

The Rise of the Engineer: Inventing the Professional Inventor During the Industrial Revolution*

W. Walker Hanlon
Northwestern University, NBER, CEPR

October 11, 2024

Abstract

Why was the Industrial Revolution successful at generating sustained growth? Some have argued that there was a fundamental change in the way that new technology was developed during this period, but evidence for this argument remains largely anecdotal. This paper provides direct quantitative evidence showing that how innovation and design work was done changed fundamentally during the Industrial Revolution, through the emergence of a new type of inventor: the professional engineer. Using a rich set of patent data, data from biographical sources, and data on civil engineering projects, I document the emergence of the engineering profession starting in the last quarter of the 18th century and show that engineers differed from other types of inventors in important ways. These findings improve our understanding of innovation during the Industrial Revolution and provide perspective for thinking about other fundamental changes in the innovation system.

Keywords: Industrial Revolution, innovation, engineering, economic growth

*I thank Brian Beach, Asaf Bernstein, James Feigenbaum, James Fenske, Michela Giorcelli, Daniel Gross, Philip Hoffman, Anton Howes, Morgan Kelly, David Mitch, Joel Mokyr, Petra Moser, Alessandro Nuvolari, Kevin O'Rourke, Santiago Pérez, Michael Peters, Sarah Quincy, Lukas Rosenberger, Vasily Rusanov, Mike Waugh, Chenzi Xu, Ariell Zimran and seminar participants at NYU Stern, Northwestern and the Virtual Economic History Seminar for helpful comments. I am grateful to Sean Bottomley, Stephen Billington, Carl Hallmann, Petra Moser, Alessandro Nuvolari, Lukas Rosenberger, and Emre Yavuz for their willingness to share data with me. Jessica Moses, Rachel Norsby and Liliya Shumylyak provided excellent research assistance. Funding for this project was provided by the NYU Stern Center for Global Economy and Business and by National Science Foundation CAREER Grant No. 1552692.

Technological progress played a central role in the Industrial Revolution. Much of the research on innovation during this event has focused on the factors that led to the burst of inventive activity that took place in Britain in the second half of the 18th century. Yet, as Joel Mokyr has pointed out, short bursts of technological progress have occurred many times in history. “The true miracle” he argues, “is not that the classical Industrial Revolution happened, but that it did not peter out like so many earlier waves of innovation” (Mokyr, 2004, p. 15).

Why was technological progress sustained? Some have argued that the explanation for this miracle is that the system through which new technology was developed changed in a fundamental way during the Industrial Revolution. Renowned mathematician and philosopher of science Alfred North Whitehead, for example, argued that, “The great invention of the nineteenth century was the invention of the method of invention.”¹ Did such a change in the process of innovation take place during the Industrial Revolution? And if it did, what did the change look like?

The primary contribution of this paper is to provide direct quantitative evidence documenting the changes in the innovation process that took place in Britain during the Industrial Revolution. I show that a fundamental change *did* take place in the way that innovation and design work was done in Britain. This change was the emergence of a new type of specialized inventor and designer: the professional engineer.

I begin by documenting the emergence of the engineering profession using three different approaches based on a combination of patent data and biographical data drawn from the *Oxford Dictionary of National Biography* (ODNB). Interestingly, I show that the timing of this emergence corresponds closely to the onset of the Industrial Revolution, a feature that holds regardless of whether engineers are identified based on their self-reported occupations, on the judgement of historians, or using a data-driven task-based approach based on the activities that appear in their ODNB biographies. This timing corroborates the view of contemporary engineers as well as modern historians such as Watson (1989) who, in his history of the Society of Civil Engineers, describes how (p. 1), “When John Smeaton described himself as a civil engineer for the first time...he identified a new profession” which combined “The craftsman’s fund of knowledge, based on natural genius and practical experi-

¹Whitehead (1925), p. 96.

ence...with the assimilation of scientific principles.”

The emergence of this new group of professionals who specialized in design and invention work, and brought scientific insights to solve practical problems, contrasts with the innovation system that existed in the middle of the eighteenth century. Using patent data, I show that before the emergence of engineering, invention was done mainly by either manufacturer-inventors, a group that combined innovative activities with other work related to production and management, or gentleman tinkerers, who saw invention as an amusing diversion.

Using the full text of the ODNB biographies for engineers and individuals active in other related activities—science, technology development, and manufacturing—I offer a task-based approach to identifying the defining characteristics of this new occupation. This analysis shows that activities such as “design,” “invent,” and “patent” were core functions of early engineers, while engineers were also involved in activities related to the implementation of new designs and ancillary activities such as consulting, reporting, and surveying. Notably, these defining characteristics changed very little across the period I study (roughly 1700-1869) and they are similar regardless of whether I identify engineers using the judgment of historians or on individual’s own self-reported occupations in their patents. They also correspond closely with direct evidence from contemporary engineers and observers about how they thought about the features that, in their view, defined this new occupation.

Using patent data, I also show that engineers were fundamentally different from other common types of inventors. Most importantly, I document that engineers were more productive, generating more patents per decade than any other type of inventor, and patents of higher quality based on several available patent quality indicators. Individual engineers also patented across a substantially broader set of technology categories than any other type of inventor. Even within the careers of individual inventors, I show that once someone began to describe their occupation as engineer they began to operate differently, by working with more coinventors, and they became more productive. These patterns indicate that engineers represented a new type of inventor, rather than simply a relabeling of some existing type and, as Adam Smith suggested, specialization appears to have allowed engineers to be more productive in inventing new and better technologies.

I unpack this productivity advantage by examining two specific ways that engineers changed the innovation system. One of these is the use of coinventor teams. Using the patent data, I start by showing that engineers were substantially more likely to produce patents in coinventor teams than other types of inventors. I also show that patents with multiple inventors were of higher quality using multiple measures of patent quality. However, this quality advantage was driven almost entirely by teams that included at least one engineer. This illustrates one important way that the emergence of engineering impacted the innovation system.

Engineers were also particularly active in bringing science into the inventive process. The use of scientific principles and insights in the inventive process was an important change relative to an earlier approach that relied mainly on craft skills and trial-and-error experimentation. I document the role that engineers played in bringing scientific insights into the innovation process using data covering articles in two of the leading English-language scientific journals of the era which I have linked to patent data. These data show that engineers were the largest group of authors of scientific articles who also filed patents, a result that is consistent with the view of contemporary engineers that they were the mediators between “philosophers” and “working mechanics.”²

These findings raise questions about what caused the emergence of the engineering profession in Britain during the Industrial Revolution. The answer, like explanations of the onset of the Industrial Revolution itself, is likely to be complex. To make progress on this important question, I start by offering a theoretical framework that describes the emergence of a group of specialist inventors (engineers) within an endogenous growth framework. The framework links the emergence of the engineering profession to several fundamental changes occurring in Britain during this period that are thought to have contributed to the onset of the Industrial Revolution more generally. In the model, the emergence of the engineering profession depends on the institutional environment, a factor emphasized by Douglass North and Acemoglu, Johnson and Robinson, among others, access to both scientific knowledge and craft skills, a factor emphasized by Joel Mokyr and others, and the rising demand for

²ICE (1928), p. 11.

new technologies.³ After presenting the theoretical framework, I then discuss a combination of historical and quantitative evidence supporting these links between the institutional environment, knowledge access, market size, and the emergence of the engineering profession.

I also provide evidence that, at least initially, the emergence of the engineering profession was a specifically British phenomenon. To do so, I compare the patterns I observe in Britain to France, the most natural comparison country during this period, using data on French patents from 1791-1843. As in the British analysis, I find that individuals describing themselves as engineers in the French patent data were more productive than other types of patent holders, produced higher quality inventions, and operated across a broader set of technology categories. This provides further evidence that engineers were fundamentally different than other types of inventors, even in France. However, I also show that French innovation system did not exhibit the same changes that took place in Britain. In particular, there was no “rise of the engineer” in France similar to the pattern observed in the U.K., at least up to the middle of the 19th century. Instead, the French innovation system remained relatively stable from 1791-1843: dominated by manufacturer-inventors, a structure that was similar the British innovation system in the mid-18th century.

To complement these results, I also examine the professionalization of civil engineering that occurred in parallel with the shifts in other types of engineering work. Using a combination of historical evidence and data covering major infrastructure projects undertaken in Britain after 1500, I provide evidence that the way civil engineering work was done changed in the second half of the eighteenth century. As Skempton (1996, p. vii) describes, “Works of engineering had been executed before 1760, some of considerable magnitude, but they could not provide sufficient employment to support a body of men trained in work of this kind...” Supporting this historical narrative, I provide evidence showing that, prior to 1750, most major civil engineering projects were overseen by engineers without substantial prior training or experience. This began to change starting in the 1760s. After that point, major civil engineering projects were increasingly overseen by experienced engineers that headed

³See, e.g., North & Thomas (1973), North & Weingast (1989), Acemoglu *et al.* (2005), Mokyr (2009), Kelly *et al.* (2023), Allen (2009a), et al.

established firms and undertook numerous major projects. They also trained the next generation of civil engineers, most of whom had gained extensive experience working for established firms before being awarded major projects of their own. Thus, we can trace out the professionalization of civil engineering work occurring in parallel with the arrival of engineers as important producers of mechanical inventions documented in the patent data.

Together, these mutually-reinforcing strands of empirical analysis highlight the fundamental changes that took place in the way invention and design work was done in Britain during the Industrial Revolution. These changes were characterized by the emergence of a new profession, engineering, where design and invention were among the core occupational functions. These changes began in roughly the third quarter of the eighteenth century, just as the Industrial Revolution was taking off, and accelerated through at least the middle of the nineteenth century. Moreover, the emergence of professional engineers as a key group of inventors appears to have been a largely British phenomenon, which may help explain why Britain pulled ahead of other European countries during this period. These empirical findings can help us better understand how the innovation system changed during this seminal event in economic history.

1 Related literature

This paper is related to two main strands of work within the broad literature on innovation during the Industrial Revolution. One existing set of papers uses biographical sources to look at the careers of important inventors or innovators (Khan & Sokoloff, 1993, 2004; Allen, 2009b; Meisenzahl & Mokyr, 2012; Howes, 2017; Khan, 2018). A second closely related set of work uses patent data to examine the British innovation system during the Industrial Revolution. Important contributions to this literature include Dutton (1984), MacLeod (1988), Sullivan (1989), Sullivan (1990), and Bottomley (2014), as well as a number of other papers discussed later. The closest existing paper to my study is Nuvolari *et al.* (2021), which finds that what they define as macroinventions were more likely to be produced by patenting inventors who describe their occupation as engineer. Another closely related study is MacLeod

& Nuvolari (2009), which focuses on the mechanical engineering industry (essentially machine and tool making). Despite including the term engineering, this sector should not be confused with the engineers I study, who, as I will show, worked across a wide range of industrial sectors and technology types.

This study goes beyond previous work by (1) identifying the emergence of engineers as an important group of inventors of patented technologies, (2) showing the engineers were fundamentally different—more productive—than other types of inventors, (3) describing some of the ways that engineers changed the way that innovation was done, (4) bringing together a wide range of additional data to show that this emergence was not confined to patented inventions or mechanical engineering alone, and (5) comparing patterns observed in Britain to another country to show that this emergence was a specifically British phenomenon.

My results have implications for two other lines of work related to the Industrial Revolution. One is a set of studies highlighting the importance of upper-tail knowledge during this period (Mokyr, 2005; Squicciarini & Voigtländer, 2015).⁴ My results provide clear support for the argument that upper-tail knowledge mattered for technological progress during this period.

Another long-standing debate, stretching back to the work of Landes (1969) and Rosenberg (1974), has to do with the importance of scientific knowledge in the Industrial Revolution. Influential contributions to this literature include Mokyr (2002), Jacob (2014), Squicciarini & Voigtländer (2015), Khan (2018), and Kelly & Ó Gráda (2022). I explore this issue in a companion paper, Hanlon (2022), using data linking the authors of articles in two of the leading English-language scientific journals of the nineteenth century to patents. While that paper analyzes the evolution of the relationship between science and technology during the Industrial Revolution, it does not examine in detail the types of scientist-inventors that were active in both fields. This paper examines that relationship in detail in Section 5.2, where I show that engineers played a key role in bringing scientific insights to the inventive process.

Finally, this paper relates to studies by Murphy *et al.* (1991) and Maloney &

⁴Mokyr (2005), for example, argues that “what mattered above all was the level of sophistication of a small and pivotal elite of engineers, mechanics and chemists.” A slightly more distant literature focuses on broader based skills, rather than the upper-tail, using information on occupation distributions, literacy, or numeracy. One recent example is de Pleijt *et al.* (2020).

Valencia Caicedo (2022) examining the impact of engineers on economic growth in more recent settings. An open question in this literature is: where did the engineering profession come from? Was it always present, or is the emergence of engineering a more recent phenomenon? My results answer this question. In particular, I show that the emergence of the engineering profession is a relatively recent occurrence by historical standards, one that corresponded closely with the timing of the onset of modern economic growth.

2 Rise of the Engineer: Three approaches

I begin by documenting, using three approaches, the emergence of the engineering profession in Britain during the Industrial Revolution. My first approach focuses on self-reported occupations using patent data. This approach has the advantage of covering a wide set of inventors and revealing how individuals thought of their own occupation. However, it covers only individuals who patented, and we may worry that self-reported occupations can change simply because certain occupational titles became more fashionable over time. In a second approach, I instead use biographical data from the *ODNB*. This approach has the advantage of covering individuals who did not patent, though biographies are only available for a smaller set of highly successful individuals.⁵ In these data, engineers are identified based on the judgement of modern historians, a measure that is less likely to be influenced by changes in the popularity of occupation titles over time. Finally, I offer a data-driven task-based approach which uses verb stems extracted from the *ODNB* biographical data to predict who should be considered an engineer. The main advantage of this approach is that it is immune to the concern that the number of engineers may be growing over time simply because engineer was becoming a more popular occupation title. Finally, I describe how the results from these three approaches match the observations made by contemporary engineers regarding the origins and character of their own profession.

⁵However, this upper-tail group is likely to have played a particularly important role in technology development (Mokyr, 2005; Squicciarini & Voigtländer, 2015), so they are a primary focus of this paper.

2.1 *Engineers in the patent data*

Figure 1 describes the rising importance of engineers as inventors of patented technologies based on the occupations self-reported in all British patents filed from 1700-1869 (I will discuss these patent data in more detail in Section 4.1). Specifically, the figure shows, by decade, the share of patents with at least one inventor in a particular occupation group (top panel), and the number of patents with at least one inventor in each occupation group (bottom panel, log scale).⁶ The rise of the Engineer, starting in the 1760s and 1770s, is apparent. By 1800-10, 10% of patents had at least one engineer inventor. This rose to 20% by the 1840s. By the 1860s, engineers accounted for over 29% of patents for which an occupation was reported. No other group shows a similar pattern of growth across the study period. In the bottom panel we can see that patents by all types of inventors were growing during this period, but no other group experienced growth similar to the rate that we see for engineers after 1760. By the 1860s engineers produced far more patents than any other occupation group.⁷

Three broad types of inventors, described by MacLeod (1988, p. 78-9), can be discerned in Figure 1. First, there are the amateur inventors, for whom invention was “an amusing diversion that might one day open up a lucrative sideline.” Many of the gentlemen in Figure 1 probably fall into this group. The second group were the professional inventors, for whom “inventing was not a hobby but a livelihood. Typically, he obtained a large number of patents across a wide field of industries...” We will see that engineers fit this description quite closely. The third group MacLeod called the businessman, “those who were ready to engage in manufacturing or trade...while they sometimes obtained more than one patent, these usually related only to their own branch of business.” This group, which I will call manufacturer-inventors, were

⁶The shares in the top panel are relative to all patents for which an occupation is reported. This makes very little difference before the 1850s, but it matters for the last two decades because there was a large increase in patents that did not list an occupation after the 1852 patent reform.

⁷For a sense of the individuals that listed their occupation as “engineer”, Appendix D.5 provides a list of the top-five engineer patent filers in each decade. Prior to the 1760s, very few engineers appear in the patent data and even the top patenting engineers were generally obscure, with the exception of John Kay in the 1730s. However, this had changed by the 1780s, when we see the list topped by James Watt and William Playfair (inventor of the bar chart and pie graph, among other things), followed by Joseph Bramah and Richard Trevithick in the 1790s and the first decade of the 19th-century, Marc Isambard Brunel and Bryan Donkin in the 1810s, etc.

the most common type of inventor outside of engineers. In the remainder of the analysis I will make a special point to study the differences between engineers and these manufacturer-inventors.

In Appendix E.1, I compare the pattern of patents by engineers to other groups thought have made an important contribution to innovation during the Industrial Revolution, such as watchmakers, millwrights, instrument makers, and machinists, or those that may have been related to engineers such as “engine makers” or mining engineers.⁸ The main take-away from that analysis is that none of these groups are large compared to engineers, at least after 1760, and none of them experienced the type of explosive growth in patenting that engineers exhibited.

2.2 *Engineers in the ODNB*

My second approach uses biographical data from the *ODNB*, where engineers are identified based on the judgement of modern historians. Figure 2 plots the share of engineers found in the *ODNB* relative to all *ODNB* biographies (left axis) or relative to all individuals classified as either in ‘science and technology’ or ‘manufacturing and trade’ (right axis). We can see that, up to the cohort born from 1725-49, engineers account for a very small share of *ODNB* biographies. However, starting with the cohort born in 1750-74, there is a dramatic rise in the share of engineer biographies, which accounted for over 2.5% of all biographies by the cohorts born in the first half of the nineteenth century. A similar increase is apparent when we compare engineers to other individuals classified as working either in science and technology or relative to those working in manufacturing and trade (right panel). By the first half of the nineteenth century, engineers accounted for over one-third of all notable individuals associated with science or technology.

⁸On watchmakers, see Kelly & Ó Gráda (2016). The role of millwrights is emphasized by Mokyr *et al.* (2022). Kelly & Ó Gráda (2022) highlight the role of instrument makers. Kelly *et al.* (2023) discuss the importance of artisanal mechanical skills such as those possessed by machinists and machine makers.

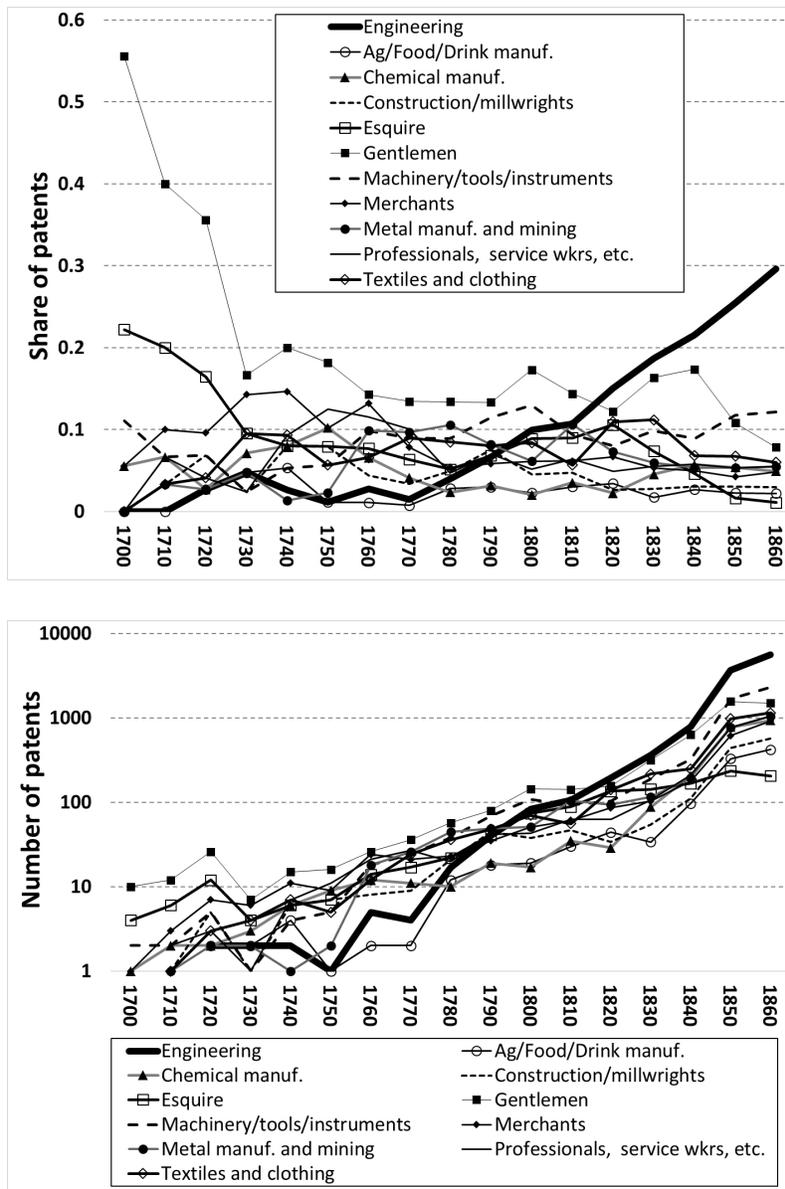


Figure 1: Number of patent observations by occupation category, 1700-1849

Based on patent data from 1700-1849. Occupation groups are based on the occupations self-reported by patenting inventors. Excludes communicated patents. Patents classified into multiple categories will be counted more than once, so the shares may sum to more than one.

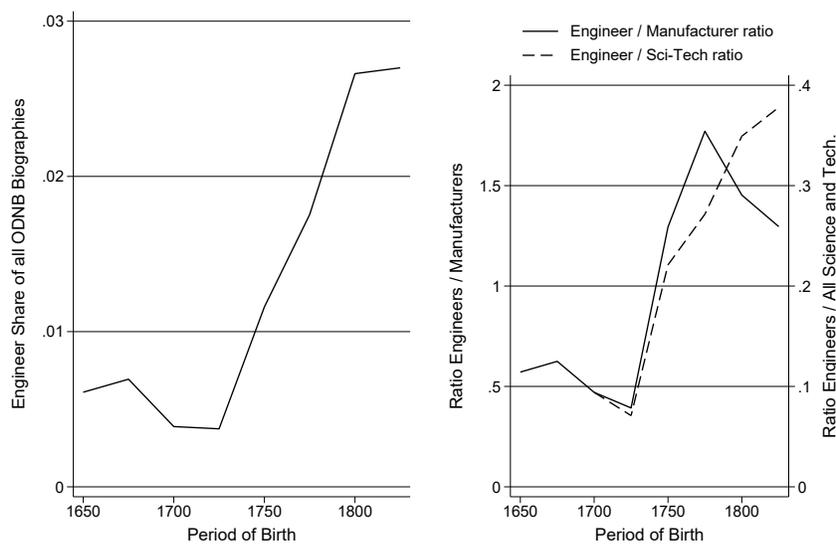


Figure 2: Share of engineers in ODNB biographies, 1650-1849

Data collected from the ODNB. Engineers, manufacturers, and others working in science and technology are classified based on the judgement of the historians who contributed to each ODNB biography.

2.3 A task-based approach to identifying engineers

Even though engineers in the ODNB data are identified based on the judgment of modern historians, one might still be concerned that these results could be influenced by changes in the popularity of a particular occupation title over time.⁹ To address this concern, I now offer a data-driven task-based approach to identifying engineers.

I begin with the full text of the ODNB biographies for every engineer born between 1650 and 1849 (439 biographies) as well as two natural comparison groups: manufacturers (349 biographies) and those non-engineers classified as involved in science or technology (1547 biographies).¹⁰ I then use natural language processing methods,

⁹This would be a concern if, for example, historians' assessments are influenced by how inventors in the past described their own occupation.

¹⁰Within the ODNB, these are the two natural comparison groups. Most engineers were classified as part of those involved in science and technology, so it is natural to compare to that group.

discussed in more detail in Appendix C, to parse the ODNB biographies to identify all of the activities—as reflected by verb stems—that appear in each biography (similar to the approach used by Michaels *et al.* (2019)). Then, using a training sample of all individuals born after 1825, I apply LASSO regressions to predict whether an individual was an engineer (as identified by historians) based on the verb stems that appear in their biography.¹¹ To ensure that the results are not driven by the verbs engineer or invent, I drop these verb stems when generating my predictions. Finally, I apply the relationship estimated on the training set to predict whether earlier individuals appearing in the ODNB were likely to be engineers.

This approach has two main advantages relative to the previous approaches. First, outside of the training sample, engineers are identified based on the verbs that appear in their biography, rather than the labels applied by either themselves or by historians. Second, the estimates used to predict whether a person is an engineer are time-invariant, so they cannot be influenced by shifts such as a change over time in the popularity of engineer as an occupational label.

Figure 3 presents the share of engineers out of total ODNB biographies predicted by this exercise. Since the model generates a numerical prediction for whether an individual is an engineer, I consider two alternative cutoffs, either one or two standard deviations above the mean predicted level across all biographies, for identifying likely engineers. For both cutoffs, we observe a consistent increase in the share of engineers among all ODNB biographies (left panel) starting with the cohort born from 1725-1749, who would have been coming into adulthood during the first few decades of the Industrial Revolution. This provides a third piece of evidence showing the emergence of the engineering profession.

Manufacturers were the other major group of inventors during the study period, as the patent data will show. I exclude military engineers from the engineers group. I also include iron masters as manufacturers. Of those individuals classified as working in science or technology, I do not include manufacturers, artists/engravers, alchemists, or fossil collectors.

¹¹See Appendix C.2 for more details. This procedure generates results that appear reasonable. For example, among the top ten individuals outside of the training sample who are predicted to be the most likely to be engineers, we find a number of famous engineers, among them Thomas Telford, John Smeaton, Isambard Kingdom Brunel, Richard Trevithick, and George Stephenson. Outside of the training sample, the predicted values are also highly correlated with historians' judgement about who was an engineer.

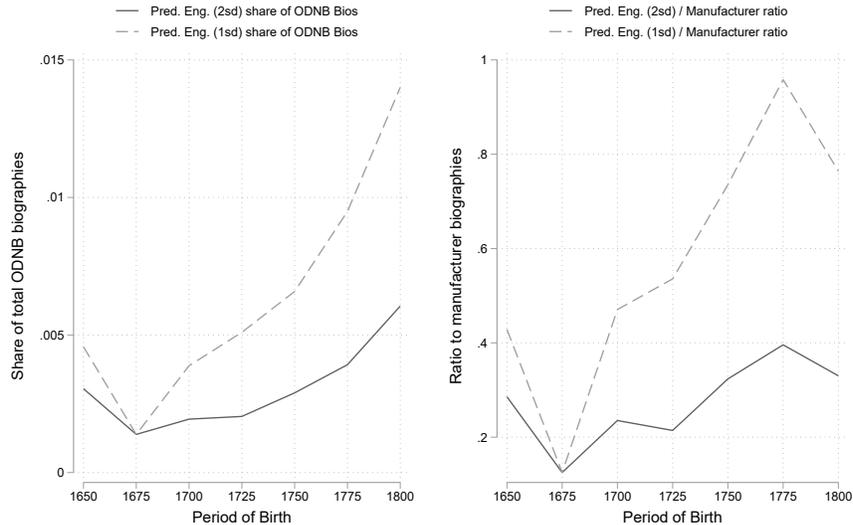


Figure 3: Share of predicted engineers in ODNB biographies, 1650-1849

Based on the full-text of ODNB biographies. Engineers are predicted using the verb stems appearing in the biographies for a training set of individuals born after 1825. The estimated relationship is then used to predict the probability an individual was an engineer in the earlier data.

2.4 Historical evidence and discussion

The quantitative results presented in the three previous figures is matched by the descriptions provided by contemporary engineers. In his *Three Lectures on the Rise and Progress of Civil and Mechanical Engineering*, William Fairbairn, one of the leading engineers of the nineteenth century, wrote that “At the commencement of 1750 the title of Engineer was unknown to the vocabulary of science; it was reserved for [James] Brindley and [John] Smeaton to establish a distinct profession under that name.”¹² Similarly, the Introduction to the first volume of the *Transactions of the Institution of Civil Engineers* describes how, prior to 1755, “Works of engineering...had previously been executed, some of them of considerable magnitude” but “they were of so unusual an occurrence as not to furnish sufficient employment to support in this country a

¹²Fairbairn (1859), p. 10. He continues (p. 10-11) “Previously to that time the engineering of the country was chiefly effected by Architects.”

race of artists trained in works of the kind.”¹³

The growth of engineering into a distinct and respected profession was accompanied by the development of institutions that helped engineers meet one another and exchange ideas. The Society of Civil Engineers was founded in 1771, followed by the Institution of Civil Engineers 1818 and the Institution of Mechanical Engineers in 1846. These provided a forum for engineers to engage, a way to present and publish their new ideas, and a representative of their interests. There was also a growing specialized press focused on disseminating engineering knowledge, including William Nicholson’s *Journal of Natural Philosophy*, founded in 1797, Alexander Tilloch’s *Philosophical Magazine* (1798), and, later, *Mechanic’s Magazine*, founded in 1823 by Joseph Clinton Robertson, an engineer. Thus, by the middle of the nineteenth century British engineers were immersed in a rich intellectual milieu based on networks formed through the learned societies and information transmitted through a vibrant scientific and technical press, while the profession itself rested on institutional foundations that would survive to today.

3 Defining an Engineer

The results in the previous section show that a new occupation—engineering—emerged in Britain starting around the time that the Industrial Revolution began. But what defined this new occupation? There are several ways an occupation can be defined: based on the tasks that people undertake, based on the inputs they use or the products they produce, based on an educational qualification or professional certification, or based on how workers in that occupation related to workers in other related occupations. Below, I begin by defining the engineering occupation using a task-based approach that focuses on the key activities that differentiates engineers from other similar workers.¹⁴ I then consider alternative definitions offered by contemporary engineers and other observers.

¹³ice (1836), p. iv-v.

¹⁴It is useful to note that educational qualifications or professional certifications, which might be used to identify engineers in modern settings, cannot be used to identify engineers in the historical setting I consider. That is because the emergence of the engineering profession that I document predated the development of an organized engineering education and certification system.

Starting with the set of verb stems extracted from the ODNB biographies for all engineers, as well as all other individuals associated with manufacturing, science, or technology, I apply a regression approach to identify those activities (verbs) that had the strongest association with engineers. Table 1 presents the twenty verb stems most strongly associated with engineers.¹⁵ For all of these, the association is statistically significant at the 99% level after adjusting for multiple hypothesis testing (sharpened p-values below 0.01). The presence of verbs such as “design”, “invent” and “patent” indicate the important role of inventive activities to the engineering profession; out of all the verbs, the one most closely associated with engineers is “design”. There are also terms indicating the role that engineers played in implementing their new designs and inventions: words such as “build,” “erect,” “employ,” “lay,” and “supervise.” Other important roles played by engineers are indicated by the presence of “consult,” “report,” and “survey.” These terms give us a sense of the types of activities or functions that set engineers apart from other highly successful individuals.

The words least associated with engineers can also be informative. When compared to manufacturers, the five verbs most associated with that group, relative to engineers, are “sell,” “expand,” “produce,” “manufacture,” and “buy.” For non-engineers involved in science and technology, the verbs most associated with that group, relative to engineers, are “publish,” “graduate,” “write,” “study,” and “collect.” The contrast between these terms and the words in Table 1 highlights the defining differences, in terms of activities, between these various groups.

Three other results emerge from my analysis of these textual data.¹⁶ First, splitting the sample by time period, I find no evidence that the verbs associated with engineers changed substantially over time. Most importantly, design and invention remained core functions of the occupation throughout the study period (see Appendix Table 10). Second, using data where I have matched patentees to ODNB biographies, I find that the results are very similar regardless of whether I identify engineers based on the labels applied by historians in the ODNB or the self-reported occupations from the patent data (see Appendix Table 11). Thus, the core functions of engineers appear to be similar regardless of whether we are relying on the patent data or the

¹⁵See Appendix C for additional results and alternative specifications.

¹⁶See Appendix C for additional details and results.

Verb	t-stat	Verb	t-stat	Verb	t-stat	Verb	t-stat
design	14.61	employ	6.74	complete	5.10	advise	4.40
build	11.53	report	6.23	open	5.01	supply	4.36
construct	9.58	erect	6.10	supervise	4.87	connect	4.24
consult	8.16	survey	5.59	improve	4.83	propose	4.11
patent	6.74	drive	5.27	lay	4.56	invent	4.01

Table 1: Top twenty verb stems associated with engineers

This table presents the 20 words most strongly associated with engineers as well as estimated t-statistics from OLS regressions based on robust standard errors. Engineers are compared to manufacturers and non-engineers categorized as involved in science or technology in the ODNB. All of the coefficients associated with these verbs have sharpened p-values below 0.001. N=789,230 (2335 biographies x 338 verbs).

ODNB to identify who qualifies as an engineer, or whether engineers are compared only to other patent holders, or to other individuals in the ODNB.

This task-based approach provides just one way of defining the engineering profession. Alternative definitions offered by engineers and observers during the period I study focus instead on the products that engineers produced, or how they related to other professions. Rees’ *Cyclopaedia* of 1819, for example, defined *Engineer* as “in its general sense...applied to a contriver or maker of any kind of useful engines or machines,” together with a separately defined *Civil Engineer*, “an order or profession of persons highly respectable for their talents and scientific attainments...as the canals, docks, harbours, light houses, etc. amply and honorably testify.”¹⁷ The Charter of the Institutions of Civil Engineers defined engineering as “the art of directing the great sources of power in Nature for the use and convenience of man.”¹⁸ In a paper presented at the first meeting of the Institution of Civil Engineers, Henry Robinson Palmer defined an engineer in relation to other occupations: “An Engineer is a me-

¹⁷Rees (1819), Vol. XIII. The origins of the English word engineer, dating to the 14th century, can be traced back to the Old French term *engigneor* and later *enginir/inginiir* from modern French and Italian (Onions, 1966, p. 314). The word originally signified military engineers, those who designed or constructed military (e.g., siege) engines. To differentiate themselves from military engineers, the earliest civilian engineers that I study sometimes called themselves civil engineers. Later, as engineering branched in different directions, civil engineer evolved to refer specifically to engineers working on the design or construction of infrastructure.

¹⁸Quoted from ICE (1928), p. 17.

diator between the Philosopher and the working Mechanic; and like an interpreter between two foreigners must understand the language of both.”¹⁹ While disparate, these statements reveal some of the defining features of the new profession, as seen by those witnessing its emergence.

To summarize, both the descriptions that contemporary engineers provide about their own occupation and the quantitative analysis of biographical descriptions from modern historians indicate that engineering was an occupation where design and inventive activity were core functions, together with associated activities such as overseeing construction, consulting, and surveying. As inventors and designers, engineers filled a gap between scientists and working mechanics and provided a bridge between theoretical insights and practical applications.

4 Differences between engineers and other inventors

In the next set of results, I use British patent data to look at differences between engineers and other types of patenting inventors. I begin by describing the data I use in detail, before looking at how engineers differed in terms of patents per person, patent quality, and the breadth of technologies that they worked on.

4.1 Patent data

Patent data provide a unique window into the development of technology during the Industrial Revolution, including details on thousands of individual inventors and inventions. Of course, not all innovations were patented (Moser, 2012), and not all patents were for useful innovations (MacLeod *et al.*, 2003). For this reason, it is important that the patent data analysis is complemented with results from the biographical data, discussed above, as well as evidence on civil engineering, in Section 8. However, many of the most important inventions of the Industrial Revolution, as well as thousands of other useful, if less famous, ideas, can be found in patent filings.

The patent data used in this study include the full listing of patents filed from 1700-1851, with details including inventor name, inventor occupation, patent title,

¹⁹Quoted from ICE (1928), p. 11.

and inventor address.²⁰ The core of this data set was digitized from the two-volume *Titles of Patents of Invention, Chronologically Arranged*, produced by the British Patent Office (BPO) and published in 1854.²¹ I focus mainly on the information about inventor occupations, while also using the names to track the output of each inventor. Excluding patents communicated from abroad, this data set includes 12,622 patent-inventor observations covering 11,243 patents.

One reason to focus primarily on the 1700-1849 period is that patent laws were largely stable during that period.²² In 1852, there was an important patent reform act that lowered the cost of patenting substantially, leading the number of patents filed annually to increase from several hundred to several thousand (see Appendix Figure 6).²³ Thus, while I have digitized additional data for the 1850s and 1860s, and I will use them in some of the analysis, it makes sense to focus my main results on the 1700-1849 period.²⁴

The most important step in preparing the data for analysis was linking patents associated with the same individual. Because making these links as accurate as possible is important for this study, this was done using a careful manual linking procedure, described in detail in Appendix D.2. For each of the patent-inventor observations from 1700-1849, I match up patents filed by the same inventor using inventor name, year of patent, inventor address, patent subject matter (based on the patent title), and in some cases additional biographical information. Because I link manually using a fairly rich set of linking information, the chance that patents are incorrectly linked to a common inventor is low, though it is possible that I have failed to link some patents by the same inventor because insufficient information to form a conclusive link was available. However, there is no reason to expect that missing links are common or systematic across inventor types. This matching process

²⁰Because I often estimate results by decade, I end my main dataset in 1849.

²¹Woodcroft (1854b).

²²Dutton (1984).

²³Papers by Nicholas (2011) and Kugler (2023) show that Britain's 19th-century patent law reforms had a significant impact on the types of inventors who patented as well as the quality of patents filed.

²⁴Patent data for years after 1851 were digitized from the *Chronological Index of Patents* prepared by the British Patent Office. A second reason to focus primarily on the 1700-1849 period is that, before the 1852 patent law change occupations were provided for most patent entries, but after 1852 the share of patents with missing inventor occupation data is substantial (around 20%).

identifies 8,328 unique inventors active during 1700-1849. Appendix Table 16 lists the most prolific patent filers during that period.

The raw patent data include over 2,000 unique occupation strings. Several of these, such as “gentleman”, “esquire”, and “engineer” appear regularly. Many others, particularly those reflecting specific manufacturing trades (e.g., “Britannia-ware manufacturer”, “Candle-wick maker”) appear irregularly. To make this set of occupation strings manageable, I have cleaned them and grouped them into broad sets of related occupations. Appendix D.4 describes these occupation groups and provides examples of specific occupations falling into each group.

Comparing the names and occupations listed in the patent data reveals that the occupations associated with specific inventors were sometimes not constant across all of their patents. This typically reflected changes in occupation over the career trajectory of an inventor. This pattern was particularly pronounced for the first generation of engineers. An example is provided by the engineer Joseph Bramah, famous as a lock and tool maker and one of the most important first-generation engineers. Bramah was trained as a carpenter and worked installing waterclosets before he turned his attention to developing new inventions.²⁵ He first appears in the patent records in 1778 (patent 1177) as a cabinet maker (consistent with constructing waterclosets). He appears as a cabinet maker again in 1783 and 1784 and then as an engine maker in 1785, 1790 and 1793. Only in 1795 does Bramah begin appearing in the patent record as an engineer. Tellingly, this was when he patented his most important invention, a hydraulic press. This patent, No. 2045 of 1795, took the hydrostatic principles discovered by Simon Steven and Blaise Pascal in the 16th and 17th centuries and translated them into practical machinery. In doing so, Bramah laid the foundation for essentially all modern hydraulic machinery. Thereafter his interests broaden and he appears in the patent record eleven more times, always as an engineer, with inventions ranging from a beer engine, a planing machine, a paper-making machine, a banknote numbering machine, and a fountain pen. This progression from manufacturer-inventor to engineer was a common pattern in the early days of engineering.

To deal with these changing occupations, when analyzing data at the patent level I

²⁵See his ODNB biography.

generally assign patents to the occupation group based on the occupation that appears in that patent’s entry. When an analysis is conducted at the level of individual inventors rather than patents (such as when looking at patents per inventor), it is necessary to identify a unique occupation for each inventor. In those cases, I typically use the modal occupation that appears across the patents that the inventor filed.²⁶ In robustness exercises, I consider alternative approaches. In some of the analysis I also exploit changes in an inventor’s occupation over time to study whether inventors begin to behave differently once they start describing themselves as engineers.

I also use data that provide comprehensive categorizations of the technology type represented by each patent, constructed by the British Patent Office.²⁷ The BPO index categorizes each patent into one, and occasionally more than one, out of 147 technology categories.²⁸ To my knowledge this is the first use of the full digitized BPO categorization data for the period before 1852. As a check on the results obtained using the BPO classifications, I also replicate my analysis using an alternative classification from Billington & Hanna (2018) generated by applying machine learning to the patent titles.

This study also uses several patent quality measures. During my study period, standard patent quality measures such as patent citations are not available. Instead, I use four alternative approaches to measuring patent quality. The first is based on the payment of patent renewal fees. The fees I study were introduced by the 1852 patent reform, so this measure is available only for patents in the 1850s and 1860s.²⁹ The second set of quality measures that I use, based on references to patents in contemporary or modern publications, are from Nuvolari & Tartari (2011) and Nuvolari *et al.* (2021). This is the only quality indicator that is available across the full study period. The third quality measure is based on exhibits in the Great Exhibition

²⁶If an inventor does not have a unique modal occupation, then that inventor is excluded from the analysis. However, this results in the exclusion of just 362 out of the over eight thousand inventors in my analysis.

²⁷These categorizations were published as the *Subject Matter Index of Patents of Invention* in 1854 (Woodcroft, 1854a).

²⁸Appendix Table 20 provides a listing of the top ten technology categories, by patents filed, in the three 50-year periods from 1700-1849.

²⁹These data come from Hanlon (2015). See that paper for further details on the source and construction of the renewals data.

of 1851, which has previously been used by Petra Moser to study innovation patterns (Moser, 2005, 2012). This measure is constructed by manually linking patent holders to Moser’s database of exhibits of patented inventions in the Great Exhibition.³⁰ A fourth measure of patent quality is constructed by matching patent holders with at least two patents to the individual profiles of famous Britons in the ODNB.

4.1.1 Productivity differences: patents per inventors

Table 2 describes the average number of patents per inventor for inventors in each occupation group, where occupations are based on the modal occupation listed across each individual’s patents. We can see that Engineers generated far more patents per inventor than those in any other occupation group.

Occupation group	Avg. patents per inventor	Occupation group	Avg. patents per inventor
Ag/Food/Drinks	1.258	Merchants	1.246
Chemical Manuf.	1.586	Mining & Metals	1.436
Construction	1.188	Misc. Manuf.	1.372
Engineers	2.069	Textile Manuf.	1.463
Esquire	1.727	Prof. services	1.349
Gentry	1.571	Other	1.265
Machinery & Tools	1.473	Unknown	1.152

Table 2: Average patents per inventor in each occupation group, 1700-1849

Inventor occupations groups are based on each inventor’s modal occupation. Those without a unique modal occupation group are excluded. Communicated patents are not included. Data cover 1700-1849, the years when matched data are available.

Table 3 verifies that the difference between engineers and other types of inventors is statistically significant and present in various sub-periods. The first column presents results looking across the full sample period. The estimates show that, indeed, engineers produced significantly more patents than other types of inventors. Moreover, the magnitude of the coefficient on engineers, 0.689, is very large relative

³⁰See Appendix E.7 for further details on the exhibition data.

to the average number of patents per inventor, which is 1.52 across the full sample. For comparison, I also estimate results for manufacturer-inventors, a group that includes the Machinery & Tools, Metals & Mining, Chemicals, Textiles, and Misc. Manufacturing occupation groups. Unlike engineers, manufacturer-inventors are not more productive than other types of inventors.

We may worry that this difference is simply because engineers were operating in technology areas where patenting was more common.³¹ In Column 2, I include controls for the modal technology category that each inventor was working in. This has very little impact on my estimates, which indicates that differences in the propensity to patent across technology categories is not behind the higher productivity of engineers relative to other types of inventors. It is also useful to look at how these patterns look in various sub-periods of the sample. The results in Columns 3-6 show that I also obtain clear results within each twenty-year period from 1770-1849 (as shown above, there are few engineers before 1770 so I do not include results for that period). In contrast to engineers, those with manufacturing occupations did not generate more patents than the average inventor in any sub-period.

While the results in Table 3 identify engineers using the modal occupation appearing in an individual's patents, and excluding those without a unique modal occupation, there are other reasonable alternative ways to classify engineers. I explore several of these in Appendix E.2 and find that all of the alternatives I consider show that engineers patented substantially more inventions than other types of inventors. In addition, I show that my results are unaffected by the decision to exclude engine builders and mining engineers from the engineers category.

In the results above, engineers are identified based on self-reported occupations. Because of this, one potential concern is that more productive individuals may choose to call themselves an engineer. To address this concern, in Appendix Section E.3 I show that similar results are also obtained if I instead identify engineers based on the judgement of the historians who produced the ODNB biographies, or if I predict whether someone is likely to be an engineer based on the verb stems appearing in their biography, and compare them to others with ODNB biographies. Thus, the higher observed productivity of engineers is not due to more productive individuals

³¹As Moser (2005) has shown, patenting rates can vary substantially across sectors.

	DV: Number of patents per inventor					
	All years (1)	All years (2)	1770- 1789 (3)	1790- 1809 (4)	1810- 1829 (5)	1830- 1849 (6)
Engineer	0.689*** (0.0865)	0.609*** (0.0879)	0.999** (0.440)	0.763*** (0.231)	0.344*** (0.131)	0.467*** (0.0924)
Manufacturer	0.0618* (0.0325)	0.0321 (0.0373)	-0.0406 (0.0597)	-0.0117 (0.0587)	-0.0319 (0.0568)	0.00400 (0.0525)
Tech. cat. FEs		Yes	Yes	Yes	Yes	Yes
Observations	7,966	7,966	652	1,210	1,803	4,215
R-squared	0.018	0.044	0.214	0.102	0.075	0.057
Testing difference between engineer and manufacturer coefficients						
F-statistic	51.6	37.9	5.43	10.94	8.14	20.89
P value	0.000	0.000	0.020	0.001	0.004	0.000

Table 3: Number of patents per inventor regressions

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS regressions with robust standard errors in parenthesis. The unit of observation is an inventor. Data cover 1700-1849. The outcome variable is the number of patents per inventor across all years (Column 1-2) or with 20-year periods (Columns 3-6). The explanatory variables are indicators for whether the inventor's modal occupation is engineer or manufacturer. Inventors without a unique modal occupation are not included. The regression in Column 2 controls for the modal technology category for each inventor looking across all of that inventor's patents by including a full set of technology category fixed effects. In Columns 3-6, I control for the modal technology category for each inventor within each period. In all of these, if there is a tie for the modal category then one is selected randomly. Data cover 1700-1849, when matched data are available.

self-reporting their occupation to be engineer.

4.1.2 Productivity differences: patent quality and inventor success

Next, I provide evidence showing that, in addition to producing more patents, engineers also produced higher quality patents and achieved greater overall career success. In Column 1-2 of Table 4, I measure patent quality using the payment of renewal fees to keep patents in force after, respectively, three or seven years. Renewals were expensive: £50 at three years and £100 at seven years, compared to the initial patent

application fee of £25.³² As a result, only 18% of patents were renewed at year three and just 6.3% at year seven. The results in Columns 1-2 show that patents with at least one engineer inventor were substantially more likely to be renewed. The effects are large in magnitude compared to the sample averages and strongly statistically significant. While patents by manufacturer-inventors were also more likely to be renewed, they were substantially less likely to be renewed than patents by engineers. Additional results using the patent renewal data are presented in Appendix E.5.

In Columns 3 and 4 of Table 4, I consider a second measure of patent quality based on references in contemporary or modern sources. Column 3 uses the WRI (Woodcroft Reference Index) compiled by Nuvolari & Tartari (2011), which is based only on contemporary sources. Column 4 uses the BCI (Bibliographic Composite Index) from Nuvolari *et al.* (2021). The BCI augments the WRI with references in modern sources. In both cases the indexes have been standardized. The results suggest that patents with at least one engineer inventor were of higher quality than other patents. These patterns are particularly strong in the BCI index, which Nuvolari *et al.* (2021) argue is the more reliable measure. In contrast to the results in Columns 1-2, these measures suggest that manufacturer-inventors generated lower-quality patents than the average. More complete results obtained using the patent quality indices are available in Appendix E.6.

In Column 5, I use exhibiting in the Great Exhibition of 1851 as an indicator of quality. The sample is the set of all inventors who patented from 1830-1849 and the outcome variable is an indicator for whether a patent holder subsequently appeared as an exhibitor or inventor in the Great Exhibition. The regression estimates reflect how the probability of being in the Great Exhibition varies by occupation group. The results show that engineer patent holders were substantially more likely to exhibit patented inventions in the Great Exhibition than other patent holders. Further details and additional results using the Exhibition data can be found in Appendix E.7.

Finally, in Column 6, I look at an indicator of the overall career success of patent holders, as indicated by their inclusion among the noteworthy individuals in the ODNB. For each of the 2,053 inventors with two or more patents, I manually search

³²For comparison, average annual nominal earnings for a worker in full time employment in 1851 were about £33. See measuringworth.com.

for each individual in the ODNB. Engineers, identified based on the occupations listed in the patent data, made up 15.5% of the group that I attempted to match to the ODNB database, but they account for 26.9% of those found in ODNB, and 34.2% of those matched who were born after 1780, an indication that engineers were more likely to achieve substantial career success than other types of inventors.

Column 6 of Table 4 provides further evidence on this pattern. The regression presented in that column is run over all inventors searched for in the ODNB database (those with two or more patents) and the outcome is an indicator for whether an individual is found in the ODNB. The explanatory variable is the modal occupation of each inventor. These results indicate that engineer inventors were about 8 percentage points more likely to appear in the ODNB than other inventors with at least two patents, while manufacturer-inventors were less likely to be noteworthy enough for inclusion. These are large differences given that the sample average rate of inclusion is 12.8%.³³ Further ODNB results are available in Appendix E.8.

One potential concern with these results is that I identify engineers using the self-reported occupations in the patent data. To ensure that this is not driving my findings, in Appendix Table 27 I instead present results where engineers are identified either based on the judgement of the modern historians, as reflected in the ODNB classifications, or using the predicted probability that individuals are an engineer based on the verb stems appearing in their ODNB biographies. Using either approach, I find strong evidence that engineers produced higher quality patents compared to other non-engineers with ODNB biographies.

Overall, the results in Table 4, together with the more complete regression results available in the associated appendices, shows that, across a range of different quality indicators, engineers generated higher quality patents and had greater overall career success than other types of inventors. This is true relative to all inventors or to manufacturing-inventors in particular, and whether engineers are identified based on their self-reported occupation, based on the judgement of modern historians, or using my data-driven task-based approach.

³³This sample mean differs from the 11.9% of inventors with 2+ patents found in the ODNB because it includes only inventors with a unique modal occupation.

	Patent renewals		Reference indices		Great	ODNB
	Year Three	Year Seven	WRI	BCI	Exhibition	Biography
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.0461*** (0.00898)	0.0198*** (0.00637)	0.0375 (0.0307)	0.235*** (0.0436)	0.0415*** (0.0132)	0.0815*** (0.0262)
Manufacturer	0.0136* (0.00772)	0.00824 (0.00519)	-0.0514** (0.0252)	-0.105*** (0.0305)	0.0133 (0.00842)	-0.0367** (0.0149)
<i>*See table notes for details on fixed effects included in different specifications.</i>						
Observations	54,735	41,213	18,474	18,474	4,453	1,985
R-squared	0.020	0.015	0.134	0.059	0.003	0.013
Testing difference between engineer and manufacturer coefficients						
F-statistic	10.1	2.50	7.50	56.8	4.16	19.74
P value	0.002	0.114	0.006	0.000	0.042	0.000

Table 4: Patent quality regressions

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS regressions. Results in Column 1 use data on renewals paid at year three for patents filed from 1856-1869. Results in Column 2 use data on renewals paid at year seven for patents filed from 1853-1866. In Column 1-2, patents that are classified into multiple technology categories appear more than once. To deal with this, standard errors are clustered by patent. The regressions in Columns 1-2 included both year and technology category fixed effects. Results in Column 3 use the (standardized) WRI index from Nuvolari & Tartari (2011) as the outcome variable. Results in Column 4 use the (standardized) BCI index from Nuvolari *et al.* (2021). The data in Columns 3-4 cover 1700-1849. Patents that fall into multiple technology categories appear more than once in these data. To deal with this, standard errors are clustered by patent. Results in Column 3-4 also include year and technology category fixed effects. In Column 5, the sample is composed of all individuals who filed patents from 1830-1849 and the outcome variable is whether they match to a patented invention exhibited in the Great Exhibition of 1851. Since the Exhibition analysis is based on matching individual inventors, the explanatory variable in Column 5 is the modal industry of the inventor. In Column 6, the sample includes all inventors with two or more patents and the outcome variable is whether the inventor appears in the ODNB. The explanatory variables are based on the modal occupation of each inventor.

4.1.3 Productivity differences: technology scope

Next, I use the British Patent Office technology categorizations to study differences between engineers and other inventors in terms of the number of technology types that they worked on. It is useful to begin by identifying the technology categories

in which engineers were particularly active. Engineers accounted for a high fraction of patents in key Industrial Revolution technology categories, including mechanical tools for boring, drilling, and punching, steam engines, boilers, railways and rolling stock, gas manufacture and use, as well as advances related to civil engineering such as bridges and tunnels (see Appendix E.12). However, engineers patented across a wide range of different technology types.

Table 5 presents the average number of technology categories patented in by inventors falling into each occupation group. Clearly engineers worked across a broader set of technology categories than any other type of inventor. This was not due to the fact that many patents by engineers were filed later in our study period. Regression results in Appendix E.13 show that not only did engineers work on significantly more technology types when looking across the full sample period, but the same is true in every two-decade sub-period from 1770 forward (we know from above that there were few engineers before 1770). In contrast, inventors holding manufacturing occupations consistently patented in fewer technology categories, most likely those closely related to their manufacturing activities.

Thus, engineers were not merely generating more inventions of the same type. Instead, they were producing both more inventions and inventions that spanned a broader set of technologies. In this, they appear to have been fundamentally different than other types of inventors.³⁴ It is worth noting that engineers typically did not produce patents in more technology types per patent filed. Rather, their diversity on technology categories covered was closely tied to the fact that they were producing more patents overall. However, this does not detract from the fact that they were able to patent in a broader set of technologies, because it may be that their greater overall productivity was possible exactly because they possessed the ability to pursue promising ideas across a broader range of technology types.

One might wonder about the extent to which the technology category results are dependent on the specific features of the BPO classifications. To allay this concern,

³⁴It is important to note that these results do not contradict the idea, emphasized in recent work by Jones (2009), that inventors become more specialized as knowledge advances. Rather, the growth of specialized inventors (engineers) should be interpreted as the first step in this specialization process. Moreover, the fact that engineers were more likely to work in coinventor teams is also consistent with what we would expect given the results in Jones (2009).

Appendix E.15 shows that equivalent results are obtained using a very different set of patent classifications generated by Billington & Hanna (2018). Another potential concern is that these results are driven by the fact that engineers are identified using self-reported occupations in the patent data. However, in Appendix Table 39, I show that very similar results are obtained if I instead identify engineers using the classifications in the ODNB, or based on the predicted probability someone is an engineer based on the verb stems included in their ODNB biography. Thus, my findings are not being driven by the fact that occupations in the patent data are self-reported.

Occupation group	Avg. number of tech. categories per inventor	Occupation group	Avg. number of tech. categories per inventor
Agric., food/drink makers	1.548	Merchant	1.491
Chemical manuf.	1.737	Metals and mining	1.602
Construction	1.491	Misc. manuf.	1.476
Engineering	2.470	Other occ.	1.483
Esquire	1.907	Prof. services	1.600
Gentry	1.797	Textiles	1.380
Machinery and tool manuf.	1.542	Unknown	1.515

Table 5: Average number of technology categories per inventor, by occupation type

Based on the modal occupation group of each inventor. Inventors without a unique modal occupation group are not included. Excludes patents that are communications. Data cover 1700-1849.

4.1.4 *Within-inventor results*

As the description of Joseph Bramah’s career above illustrates, when engineering was still a relatively new profession a number of engineers first appear in the patent data as manufacturer-inventors or other types, and then eventually began to consider themselves to be engineers. Using these occupation switchers, I can study whether the behavior and output of an inventor changes when they begin to describe themselves as an engineer.

To undertake this analysis, I begin by focusing on only those inventors with two or more patents (around 1900 inventors). For each inventor, I construct a dataset that covers all years from their first to their last patent and indicates the number of patents they filed in each intervening year. There are 380 inventors with multiple patents that list themselves as engineers in at least one patent. For these, I identify the first year that they list their occupation as engineer and generate an indicator variable that takes the value of one for that year and all subsequent years until the last patent that they filed. I then run regressions looking at how outcomes for each of these inventors changed after they began describing themselves as an engineer, with individual fixed effects included so that identification is driven entirely by changes within inventors over time. Specifically, I study how becoming an engineer is related to whether an inventor works with coinventors (their behavior) and how many patents they produce per year (their productivity).³⁵

The results are presented in Table 6. The first three columns of this table focus on one observable measure of the behavior of inventors—the share of their patents filed with at least one coinventor—which I will return to in Section 5.1. The results in the first column show that individuals began working with more other inventors once they became engineers. To ensure that this wasn't just due to becoming more experienced as inventors, the second column includes a control for the number of years since each inventor's first patent. In the third column, I drop observations from the first year in which an inventor listed their occupation as engineer. This changes the sample, since it eliminates those who did not have patents in years after they first list their occupation as an engineer (about 18% of engineers), but we still see evidence that inventors worked with more coinventors after becoming engineers.

In Column 4-6, I look at the output of inventors, specifically the number of inventions they produced per year, between the first and last year that they patented.³⁶ The results in the first column shows that individuals generated about 0.25 more patents per year after they started describing themselves as an engineer. This is a

³⁵Unfortunately, it is not possible to also assess how patent quality changes when inventors become engineers, since the only quality measures available across the full study period, the reference-based indexes, are too noisy to generate clear results given the sample size used in this analysis.

³⁶Note that the sample size is larger in Columns 4-6 than in Column 1-3 because the sample in Column 4-6 includes inventors who never had a multi-inventor patent.

large increase relative to the sample average of 0.32 patents per year. Column 5 shows that this is not due to a general increase in patenting as inventors' careers progressed. In Column 6, I drop from the sample the first year in which an individual described themselves as an engineer. This is done because to become an engineer the individual must appear in the patent database, which causes a direct link between becoming an engineer and generating a patent. Dropping this ensures that this mechanical effect is not behind my results. I still observe clear effects in Column 6 despite the fact that these results are likely to be biased toward zero (the true magnitude of the change should lie between the estimates in Columns 5 and 6). Additional results, in Appendix E.11, show that even stronger effects are estimated if quadratic controls for time since first patent are included.

	DV: Share of patents with multiple inventors			DV: Patents per year		
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.051** (0.0229)	0.062*** (0.0235)	0.092*** (0.0305)	0.252*** (0.0334)	0.266*** (0.0335)	0.069** (0.0328)
Years since first patent		-0.00093 (0.00061)	-0.00076 (0.00059)		-0.0012*** (0.00046)	-0.00062 (0.00043)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Dropping first year as Eng.			Yes			Yes
Observations	5,333	5,333	5,152	18,787	18,787	18,641
R-squared	0.547	0.548	0.552	0.234	0.234	0.233

Table 6: Within-inventor regressions

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered by individual. The Engineer variable is an indicator for each individual that takes a value of one starting from the first year in which an individual listed their occupation as engineer in a patent, and zero otherwise.

The fact that the same individuals begin to behave differently, and produce more, once they begin describing themselves as an engineer indicates that the broad differences between engineers and other inventors documented above are not merely due to the selection of more productivity individuals into the engineering profession. In-

stead, these results suggest that once an individual began to think of themselves as an engineer, their behavior changed in a way that led to increased inventive output.

5 Mechanisms: What made engineers more productive?

The results presented thus far raise a number of additional questions. One important question is: how exactly did the emergence of engineering change the innovation system? Or, put another way, what made engineers more productive than other inventors? There are a number of ways that specialization in invention and design work might have increased engineers' productivity in those tasks, including the benefits of experience or learning-by-doing, the development of more extensive networks, or the ability to make larger investments in fundamental knowledge. In this section, I discuss two specific mechanisms that contributed to engineers' productivity advantages which I am able to evaluate empirically: (i) teamwork and (ii) combining advanced scientific knowledge with craft skill.

5.1 *Teamwork*

One reason that engineers may have been more productive is that, because invention and design was central to their profession, they may have been better able to form coinventor teams. The potential benefits of working in coinventor teams include bringing together individuals with complementary technical skills or partnering with those who were more able to fund or commercialize inventions.³⁷ Working in teams likely became more important over time, as technologies became more complex. Indeed, across the study period coinvention was steadily rising, a pattern that has also been documented in more recent periods (Jones, 2009).

Table 7 examines the propensity of engineers to work in teams, relative to other inventors, using the patent data. In these regressions, the unit of observation is

³⁷It is not possible to clearly differentiate these alternative motivations. However, in Appendix E.10 I explore the composition of these coinventor teams. This analysis indicates that engineers often coinvented with manufacturers or gentlemen, which may reflect the formation of partnerships between inventors and those who were well-placed to commercialize a new invention, or those who could contribute financing or political connections to a project, though it could also reflect different types of skills useful in the invention process.

a patent, the outcome variable is whether the patent has more than one inventor (10.7% of all patents), and the key dependent variable is whether one of the inventors was an engineer. Column 1 presents baseline results using OLS regressions while Columns 2 and 3 add in decade and technology category fixed effects respectively. Columns 4-6 follow the same format, but using Probit regressions.³⁸ These results show that patents by engineers involved significantly more co-inventors than patents filed by other types of inventors. The results are strongly statistically significant as well as large relative to the average rate of multi-inventor patents of 0.107 across the full sample. Thus, these findings indicate that engineers went about the process of invention in a way that differed markedly from other inventors.

DV: Indicator variable for patents with multiple inventors						
	OLS regressions			Probit (marginal effects)		
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.066*** (0.0097)	0.058*** (0.0098)	0.044*** (0.0084)	0.066*** (0.0097)	0.055*** (0.0094)	0.045*** (0.0087)
Decade FEs		Yes	Yes		Yes	Yes
Tech. Cat. FEs			Yes			Yes
Observations	11,243	11,243	15,679	11,243	11,243	15,185
R-squared	0.006	0.013	0.087			

Table 7: Patenting with coinventors

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Data cover 1700-1849. In Columns 1-2 and 4-5 the unit of observation is a patent and robust standard errors are used. In Columns 3 and 6 the unit of observation is a patent-by-technology-category, so patents listed in multiple technology categories may appear more than once. To account for that, standard errors are clustered by patent. The explanatory variable is an indicator for whether one or more of the inventors is listed as an engineer in the patent entry.

There is also evidence that working in teams mattered. In Appendix E.9, I study this question using both the BCI patent quality measure from Nuvolari *et al.* (2021)

³⁸Note that in Columns 3 and 6 the number of observations increases because patents listed in more than one technology appear more than once, and to account for this standard errors are clustered by patent.

and a measure based on whether renewal fees were paid to keep a patent in force.³⁹ I find two interesting results. First, patents with multiple inventors are of higher quality than single-inventor patents. Second, this effect appears to be driven largely, and in some specifications entirely, by patenting teams that include at least one engineer.

In summary, there is clear evidence that engineers were more likely to work with coinventors than other types of patent holders. Patents with multiple inventors tended to be of higher quality than those with single inventors, but that effect is driven mainly by inventor teams that include at least one engineer. Together, these results suggest that one important way that the emergence of engineers changed the innovation system was through expanding the use and effectiveness of inventor teams.

5.2 *Combining scientific knowledge with craft skill*

A second way that engineers influenced the innovation system was by harnessing scientific insights to solve practical problems. As the quote from Henry Robinson Palmer in Section 3 suggests, engineers during my study period saw the combining of scientific knowledge and craft skills as one of the defining features of their profession. Here, I attempt to provide quantitative support for the role of engineers as bridges between pure science and practical application.

The starting point for this analysis is a dataset, from Hanlon (2022), of authors of scientific articles in two of the most important scientific journals of the era, the *Proceedings of the Royal Society (Proceedings)* and the more exclusive *Transactions of the Royal Society (Transactions)*. For each author of an article published in these scientific journals between 1800 and 1869, I have painstakingly searched for any matching inventor in the patent data and then manually verified that the author and patentee are the same individual.

Looking across all authors of scientific articles in those journals, Hanlon (2022) shows that the share of authors who also patented was substantial and growing throughout the 19th century. These scientist-inventors tended to produce more patents than other patenting inventors, and patents of substantially higher quality.

³⁹Very similar results to the BCI results are obtained using the WRI index from Nuvolari & Tartari (2011). It is not possible to study this issue using the other measures of quality, since those are observed at the inventor level rather than the patent level.

The scientific contributions of this group were concentrated in a few disciplines, including physics and mechanics, metallurgy, chemistry, sound, scientific instruments, and electricity.

Here, I use the occupations listed in the patent data to break down these results in order to identify the specific contribution of engineers relative to other occupation groups. The results, available in Appendix Table 42, show that most of the authors of scientific studies that were also engaged in patenting activities fall into two groups: engineers, and gentlemen/esquires, the latter group comprised mainly of individuals from the aristocratic classes. Together, these two groups constitute about 40% of the “bridge” between science and engineering. Medical doctors, chemists, and the “other professionals” group, which mainly includes professors, lawyers, and clergy, also played an important role. It is notable that there are very few manufacturers who were involved in both science and technology, despite the fact that this was the largest group of patenting inventors.⁴⁰

Engineers accounted for a large share, 46%-51%, of the patents generated by individuals who also published scientific articles in these two leading journals, a much higher share than any other group. This is because engineers who also authored scientific articles generated far more patents per person than other article authors. However, engineer authors tended to produce fewer scientific articles. Thus, relative to other types of scientist-inventors, engineers appear to have been relatively more specialized in technology development while dabbling in science, while others appear more specialized in science while dabbling in technology development.

These quantitative results support the view offered by contemporary engineers that the profession played a central role in applying new scientific insights to practical problems. Of course, this offers only one view of the links between science and invention during the period I study, albeit one based on the two most influential English-language scientific journals of the era. While further work on these links is needed, these results suggest that a greater willingness or ability to exploit science was likely another important contributor to engineers’ productivity advantage.

⁴⁰Of the small number of manufacturer-inventors that also produced scientific articles, almost all were manufacturers of instruments or timepieces.

6 What explains the “Rise of the Engineer”?

A second major question posed by the results above is, why did the modern engineering profession emerge at this time? This is a challenging question, one that is intimately related to even larger questions about the causes and nature of the Industrial Revolution itself. The answers are likely to be complex, defying simple mono-causal explanations or standard empirical tests.

In the next subsection, I try to make progress on this difficult problem by developing a theoretical framework that describes the emergence of the engineering profession and its consequences for technology development and economic growth. This framework incorporates ideas from influential existing work on the causes of the Industrial Revolution and describes how those causes may have also contributed to the emergence of professional engineering. To keep the exposition of the model brief, I focus on the most important aspects of the theory and relegate other details to the appendix. In the following subsection, I discuss historical and quantitative evidence supporting the role played by the forces highlighted in the model.

6.1 *Theoretical framework*

The model is a continuous time endogenous growth theory building on the Romer (1990) framework. The central feature of the model is the process through which new technologies are developed. This can be done either by high-skill non-specialists who are mainly engaged in other productive activities (manufacturer-inventors), or by specialist researchers (engineers). To join either group, an individual must expend a fraction $(1 - \iota)$ of their time in order to acquire the necessary skills. The rate at which engineers and non-specialist inventors produce new inventions is, respectively $\eta N \iota$ and $\gamma N \iota$, where N is the available knowledge stock in the economy (as is standard in endogenous growth models following Romer (1990)) and η and γ are group-specific innovation productivity parameters.

A key assumption in the model—one supported by the empirical results I have already presented—is that specialist researchers are more productive at generating new technologies than non-specialists. I.e., $\eta > \gamma$. Specialized research also involves some fixed cost, a standard assumption in models of innovation, while non-specialists

may develop new ideas simply as a by-product of their productive activities (e.g., learning by doing) without an up-front investment.

To connect my theory to existing work on the Industrial Revolution, the model incorporates two factors that seem likely to play a role in determining whether a professional research sector emerges. The first is the institutional environment, and specifically whether existing institutions provide sufficient property rights protection for inventors to profit from their new inventions. This feature connects the model to existing work, dating back at least to North & Thomas (1973), which argues that Britain’s unique institutional environment may have played an important role in allowing the Industrial Revolution to take off.

The second factor is the ease with which potential professional researchers are able to access skills and useful knowledge. This feature connects the theory to existing work, such as Mokyr (2009) and Kelly & Ó Gráda (2022), which emphasizes the importance of skills and knowledge in the Industrial Revolution and argues that Britain was particularly well-endowed with such knowledge by the eighteenth century.⁴¹ An interesting feature of the model is that access to knowledge contributes to the emergence of the professional research sector in two ways. It lowers the up-front cost that professional researchers have to pay to gain the knowledge and skills that they require. Knowledge access also increases the availability of skilled manufacturing workers, which increases the value of new technologies.

Starting from an initially low level of technology, the model exhibits three phases of development, though not all phases will necessarily occur. In the first, “pre-modern phase,” there is a low level of technology, all individuals specialize in production activities, and all new ideas are the result of serendipitous discoveries generated by workers mainly engaged in generating output. There is no professional research sector in the pre-modern phase because the limited knowledge base means that professional research is not sufficiently productive to make it worthwhile for any individual. Over time, serendipitous discoveries raise the overall level of technology in the economy (similar to the pre-modern period in Unified Growth Theory), but this process may

⁴¹Existing work highlights a variety of factors that contributed to the availability of useful knowledge and craft skills in England during this period, ranging from the influence of Enlightenment culture to Britain’s well-developed apprenticeship system.

be very slow.

As the technology level slowly rises, it *may* reach a point where enough knowledge is available to support the emergence of a dedicated research sector and the transition to modern economic growth begins. This occurs because, in the standard Romer (1990) framework, the productivity of inventors is increasing in the knowledge base that they have to work with. However, the model makes it clear that the transition to modern economic growth is not inevitable. In particular, for a specialized research sector to emerge, the cost of acquiring the necessary skills must not be too high and there must be institutions in place that allow professional researchers to profit from their discoveries.

If institutions provide inventors with sufficient protection, and they have access to knowledge at a sufficiently low time cost, then the slow accumulation of knowledge during the pre-modern period will eventually allow a dedicated research sector to emerge. If this occurs, then the emergence of a professional research sector causes an acceleration in the rate at which new technologies are developed. This acts as the mechanism through which the economy transitions toward a new balance growth path characterized by more rapid economic growth. As the transition occurs, the share of the population employed as professional researchers initially grows and then stabilizes. Concurrently, the overall share of the population acquiring skills increases and then stabilizes. Serendipitous discoveries as a by-product of production continue to occur, but over time this source of new technology diminishes relative to the contribution of dedicated researchers.

The way that slowly rising technology during the pre-modern period eventually leads (under the right conditions) to a tipping point that launches the economy toward modern economic growth is a standard feature of models that aim to describe the transition from pre-modern to modern growth, such as Galor & Weil (2000) and Hansen & Prescott (2002). This feature also connects to the historical context I study. The discovery of key macroinventions such as Newcomen's steam engine and Arkwright's water frame provided incentives for follow-on research of the type that over time would come to be dominated by engineers. Viewed through the lens of the model, these inventions represent the final increment that pushed the economy over the tipping point, allowing a professional research sector to emerge. We should not

lose sight, however, of the fact that the model does not predict that such a transition was inevitable.

Finally, it is important to recognize that the core mechanism in the model, a change in the production process through which new technology is developed, differs from existing work emphasizing, on the one hand, changes in the availability of inputs into the technology production process (such as human capital) and, on the other, changes in the rewards for producing new technology (such as increasing market size or better institutional protections for inventors). While those factors are likely to be important, and are therefore incorporated into my theory, they are distinct from the mechanism I emphasize.

6.2 *Historical discussion*

The theoretical framework links the rise of engineering to institutions, knowledge access, and the demand for engineering services. While isolating the contribution of any of these influences is extremely difficult, this section presents a mix of historical and quantitative evidence suggesting that all three of these influences were at work in the period that I study.

One factor that plays a key role in the model are institutions that allow professional researchers to monetize their inventions, particularly those that made it possible for engineers to profit without becoming manufacturers, thus freeing them to specialize in invention and design work. The patent system played a key role here.⁴² Once a new invention had been patented, inventors could monetize their inventions in several ways. One common approach was to form a partnership with an experienced businessman or entrepreneur, such as the famous partnership between James Watt (an engineer) and Matthew Boulton. A second approach was to license inventions, as famously done by Richard Arkwright, among many others (though he

⁴²Khan & Sokoloff (2004) argue that “defining and enforcing a tradable asset in new technological knowledge is also important because it encourages the evolution of a market in technology, and because it extends and increases incentives for investment in inventive activity to segments of the population that would otherwise find it difficult to directly extract returns from their technological creativity.” This division of labor was beneficial because, as one contemporary quipped, “Inventors, as a class, are singularly deficient in the qualifications for prosecuting a new trade” (Coryton, 1855, p. 22). Of course, that was not true of every engineer; some were extremely successful businessmen.

is not classified as an engineer in my data). A third alternative was to simply sell a patent outright (assignment), as the engineer Henry Bessemer did with several of his inventions (Dutton, 1984, p. 125). Patents facilitated these transfers, because patent protection allowed inventors to exhibit their technology without the risk of it being copied (Bottomley, 2014, p. 289).⁴³

Available data suggests that all of these avenues were commonly used. While no register of patent assignments and licenses exists, data from patents that were litigated in the Court of Chancery, collected by Dutton (1984) and Bottomley (2014), do provide details on whether those patents had been transferred. Appendix Table 43 shows just how common assignment and licensing was. In 1770-1829, 54% of litigated patents were transferred, and this rose to 63% in 1830-1845. All three types of transfers were common. One might expect that, because these figures are drawn from litigated patents, that the sample is skewed toward higher-value patents that were more likely to be assigned. However, Bottomley (2014) provides evidence that assignment rates did not vary substantially between lower and higher quality patents, which suggests that these high rates of assignment or licensing may have been a general phenomenon. Engineers were active users of all of the available patent assignment methods, as shown in Appendix Table 44. Overall, these figures highlight how the institutional environment allowed engineers to monetize their discoveries without the necessity of also becoming entrepreneurs (though a number of engineers did successfully run their own businesses).

The model also highlights the importance of access to knowledge to the emergence of engineering. This includes both high-quality training in craft skills as well as access to scientific knowledge. We have already seen that contemporary engineers viewed the combining of craft skill and scientific knowledge as one of the defining characteristics of their profession, and that there is evidence that engineers played a particularly important role in bringing scientific insights into the technology development process.

⁴³The patent system was not the only way that inventors were able to monetize new discoveries. There was also, at this time, a range of different prizes available for inventors working in particular technology areas. While the prizes offered by the Board of Longitude were perhaps the most famous (see, e.g., Burton & Nicholas (2017)), prizes were offered by a variety of other organizations in a range of fields, such as those for agricultural technologies offered by the Royal Agricultural Society (Brunt *et al.*, 2012).

Where did engineers access the skills and knowledge they needed? An analysis of the backgrounds of engineers, in Appendix H, shows that most early engineers began their careers by learning craft skills, either through an apprenticeship in an older occupation such as carpenter or millwright, or on the job.⁴⁴ On top of these practical skills, however, engineers needed to master, in James Watt’s view, drawing, geometry, algebra, arithmetic, and the elements of mechanics.⁴⁵ For most early engineers, these skills were learned through self-study, rather than formal education. In fact, engineers were actually less likely than other inventors, particularly gentlemen and other professionals, to have formal higher education (see Appendix H).⁴⁶ The fact that even men from modest backgrounds could access the mathematical and scientific tools highlighted by Watt almost certainly played an important role in allowing the engineering profession to emerge.

A third important factor was an increase in the demand for the invention and design services that engineers supplied. Clapham (1964), for example, describes how (p. 151), “Whilst the textile and metallurgical industries were being partially transformed, engineering, as the nineteenth century came to understand the term, was being made possible.” Certainly the British economy was growing during this period, while access to foreign markets was expanding. Increasing market size, together with high wages and cheap coal (Allen, 2009a; Fernihough & O’Rourke, 2021), likely increased the value of developing new technologies.

While a broad quantitative assessment of the contribution of increasing market size to the emergence of professional engineering is challenging, it is possible to shed some light on this influence by focusing on what today we would call civil engineering

⁴⁴Prominent engineers apprenticed in a wide variety of older occupations, such as millwrights, watchmakers, carpenters, merchants, land surveyors and civil engineers, shipbuilders, coal viewers, etc. Of these, the most common for engineers was carpenter or joiner. In later years, some engineers also apprenticed at famous engineering firms. The wide range of different apprenticeship backgrounds emphasizes the broad set of paths that led into engineering as well as the fact that engineering was not merely a relabeling of an older occupation such as millwright. Engineers were also more likely than other types of inventors to have a purely working background (beyond basic primary schooling). A number of prominent engineers fell into this group, such as the famous railway engineer George Stephenson.

⁴⁵See Jacob (2014), p. 30, footnote 24.

⁴⁶These patterns are similar to those documented for the US by Khan & Sokoloff (1993). One implication of this fact is that it would be a mistake to classify this important group of inventors based on their formal educational background, as we might in later periods.

work. The analysis discussed briefly in Section 8 as well as Appendix J shows how the expansion of the market for civil engineering work allowed the establishment of major engineering firms, led by people like James Brindley and John Smeaton, who would go on to train the next generation of civil engineers.

In summary, a combination of historical and quantitative evidence suggests that the early British engineering profession benefited from an institutional environment that allowed inventors to monetize their inventions without becoming managers, access to the craft skills and scientific knowledge that engineers required, and a growing demand for invention and design work. Together, these factors, and possibly others, contributed to making possible the emergence of a group specialized in developing new technologies—a group that came to be called engineers.

7 International comparison: Engineering in France

Was the emergence of engineering starting in the late 18th century a uniquely British phenomenon? To shed some light on this question, in this section I compare patterns observed in Britain to those on the Continent, focusing specifically on France, the most natural comparison country.

I study French patents using data that span the inception of the system in 1791 to 1843, just before a major patent reform was undertaken in 1844.⁴⁷ Similar to the British patent data, the 11,804 patents filed in France during this period include the patentee name and, in most cases, patentee occupation and location, patent title, and technology category.⁴⁸ I clean and prepare the French patent data using essentially the same procedures applied to the British data, including standardizing occupation information and conducting a laborious manual matching of patents to

⁴⁷This analysis builds on the work of Hallmann *et al.* (2021). French patent data for this period have also been used by Nuvolari *et al.* (2023).

⁴⁸The occupations appearing in the French data differ from those found in Britain, with almost no one described as a “Gentleman” or “Esquire”. However, a number of inventors described themselves as either working in government (e.g., mayor) or as a member of the military. These are probably the most comparable occupations to the “gentleman” category found in the British data given that the military and public service were two of the primary occupations for the British upper classes. The French system also distinguished between patents of *invention* of new technologies, *improvement* to existing technologies, and *importation* of technologies discovered abroad. All three types are included in my analysis.

identify unique individuals.⁴⁹ Starting with 14,161 patent-inventor observations, this matching procedure identifies 10,559 individual inventors (filing 1.35 patents per inventor on average). One way that the French patent system differed from that in the UK is that patentees could apply for protection over 5, 10, or 15 years, with higher fees for a longer duration. This feature is useful because it provides an indicator of expected patent quality.

One interesting pattern in the French patent data is that, like Britain, engineers in France also appear to be more productive than other types of inventors. This is true both in terms of the number of patents they produce as well as patent quality (as indicated by the length of the patent term). These results are presented in Appendix I.

A second interesting pattern in the French patent data relates to the contribution of foreign inventors, particularly the British. Of the inventors with an address listed in the French data, 92% had a modal location in France. The next largest group by far was the British, accounting for 5.8%, followed by the U.S. (0.5%) and all of the various German territories (0.47%). While British inventors accounted for just 5.8% of all French inventors, they accounted for 11.7% of all engineers, and 13.8% of patents by engineers, in France. Moreover, within the group of British inventors patenting in France that reported an occupation, 37.4% were engineers. Since engineers accounted for a lower fraction of all British patentees during this period, this tells us that engineers were much more likely than other British inventors to also patent their inventions abroad. This provides yet another indicator that engineers differed in important ways from other types of British inventors.

The third and most important pattern found in the French patent data has to do with changes in the contribution of engineers to overall invention over time. Figure 4 presents the key results, comparing the share of patents filed by engineers in Britain and France relative to all inventors (left panel) or those inventors who reported an occupation (right panel). Unlike Britain, we can see that France did not experience a rise of patents by engineers in the first few decades of the nineteenth century. Instead, the types of inventors that patented in France remained essentially stable throughout

⁴⁹Individual matches in the French patent data are particularly reliable because there were few common surnames and the data often included multiple first and middle names.

1790-1843 period and dominated by manufacturer-inventors (see Appendix Figure 8), similar to the patterns observed in Britain before the emergence of engineering. This contrast may help explain why it was Britain, rather than France, that emerged as the technology leader during this period.

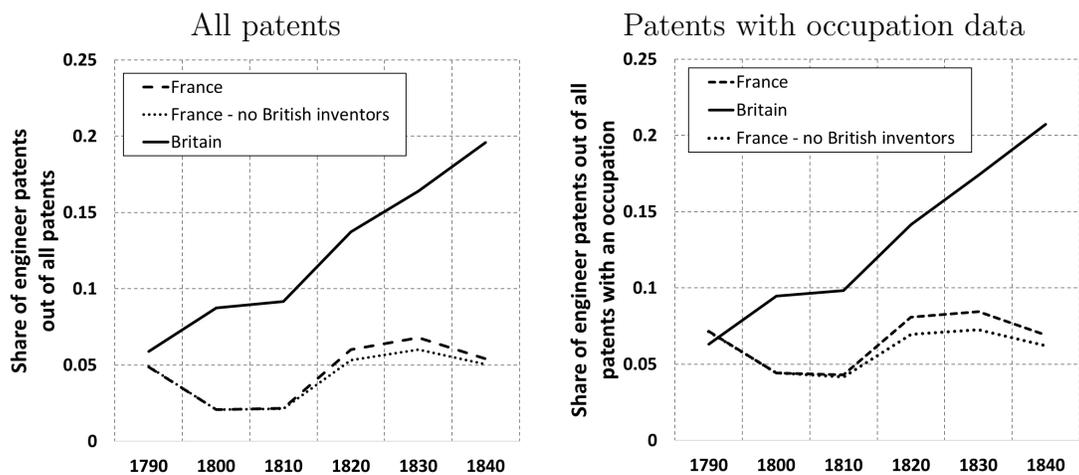


Figure 4: Share of patents by engineers in Britain and France

Source: Engineers are identified as those listing engineering as their modal occupation. The French data spans 1791-1843. The British data cover 1790-1849.

Why did engineering emerge in Britain during the early stages of the Industrial Revolution, but not in France? The most likely answer to this question lies in existing work highlighting the advantages that contributed to the early onset of the Industrial Revolution in Britain, including the institutional environment (North & Weingast, 1989), the availability of craft skills (Kelly *et al.*, 2014), high wages (Allen, 2009a), and access to coal (Fernihough & O'Rourke, 2021).

One factor that does not appear to have played a critical role was the availability of a formal system of engineering education. The fact that we do not observe the emergence of engineers as an important part of the French innovation system before the mid-1840s is particularly surprising given the well-established system of engineering education that existed in France at this time. However, as discussed in Appendix K, the French system was largely directed by the government and focused

on producing engineers skilled at designing public infrastructure, mainly for military purposes. In contrast, the engineering profession that developed in Britain did so with very little government intervention, resulting in a profession with a focus on developing economically-valuable new technologies.

8 The Professionalization of Civil Engineering

Civil engineering work is perhaps the most closely associated with the engineering profession, and it was the first to develop many of the features of a profession, such as dedicated professional societies. This section reviews available historical evidence on the development of the civil engineering profession, supported by some new quantitative analysis.

While civil engineering work has been undertaken for millennia, historians highlight the fundamental changes that took place in how this work was done during the eighteenth century. Bill Addis, in his monumental history of 3000 years of building engineering (Addis, 2007), titles the chapter covering 1750-1800, “Engineering becomes a Profession.” In it, he describes how this professionalization was reflected in the career of John Smeaton, one of the leading civil engineers of the age (p. 239-240):

[John] Smeaton was able to apply general principles, based on science and tested using full-sized and scale model experiments, to an engineering problem in a field entirely unfamiliar to him...the translation of real engineering problems into simplified theoretical models was becoming a matter of course for the few engineers who were scientifically and mathematically educated...from Smeaton’s calculations...we can see that he had already established our modern approach to engineering design...While Smeaton has become an engineering icon...many other engineers were treading similar paths.

I provide quantitative support for this narrative using a list of 338 major British civil engineering projects. These data, from Skempton *et al.* (2002), have been digitized and combined with biographical information on the engineers involved.⁵⁰ While

⁵⁰Further details on these data can be found in Appendix J.

the data cover 1500-1830, I focus mainly on the period after 1600, since there were few major projects before that point. These data show that from 1600-1760, roughly 75% of major engineering projects were overseen by someone who had not previously overseen another major project (see Appendix Figure 10). After 1760, however, the pattern changes. From that point until 1830, roughly 35% of all major projects were overseen by a chief engineer who had not already overseen a major project. Moreover, after 1760, very few major projects were overseen by engineers who did not either have prior experience or training under a more experienced engineer. Thus, the engineers chosen to oversee major projects were becoming a more experienced and more professional group.

What changed in the middle of the eighteenth century? Before 1760, major infrastructure projects were often designed and overseen by skilled craftsmen as one-off endeavors.⁵¹ Many of these “proto-engineers,” with backgrounds that included millwright, architect, surveyor, mason, and mining engineer, were skilled, and some were brilliant. What was different was that they had rarely developed their skills by working on previous major engineering works, and they rarely undertook more than one or two important engineering projects in their lifetime.

One striking example of this pattern is provided by the construction of the Westminster Bridge, the most expensive infrastructure project undertaken in Britain in the first half of the eighteenth century. Parliament chose Charles Labelye as the engineer in charge of this project. Labelye was skilled and knowledgeable, but up to that time he had not a single major engineering project to his name, either as chief engineer or as an assistant engineer under someone more experienced (Skempton *et al.*, 2002). That Parliament chose him to undertake the most important engineering project of the period was emblematic of how civil engineering was done up to that point.

After about 1760, this pattern begins to change with the emergence of a more professional body of engineers, each overseeing numerous major engineering works. From 1700-1750, for example, the most prolific individuals on Skempton’s list, Thomas Steer and John Reynolds, oversaw four major projects each. From 1750-1800, the most prolific engineer, John Smeaton, oversaw eighteen, followed by William Jessop

⁵¹Certainly there were some exceptions, such as Cornelius Vermuyden or George Sorocold.

(15 projects), John Rennie (9 projects), James Brindley (8 projects), etc.⁵² By 1800, the idea that a project such as the Westminster Bridge would have been awarded to an engineer with no prior experience would have seemed absurd.

One aspect of the professionalization of the civil engineering that took place after 1760 was that young engineers typically gained extensive experience as assistant engineers before overseeing major projects. From 1700-1760, my data show that only 20 percent of engineers undertaking their first project had prior experience working under an engineer who had previous experience on a major project. This changed in the following generation. After 1760, more than half of all engineers overseeing major projects were trained by more experienced engineers. John Smeaton, one of the most influential early civil engineers, trained five engineers who would go on to oversee major projects, including William Jessop. James Brindley, another important early engineer, trained six, including Robert Whitworth. Jessop would go on to train or partner with seven later engineers who oversaw major projects. Whitworth would train six. Thus, we can see the profession of civil engineering develop after 1760, as the knowledge and experience of the first generation of professional civil engineers was passed on to the next.

So, the rise of engineers as an important group of *inventors* shown in the patent data was paralleled by the professionalization of civil engineers as *designers* of a wide variety of civil infrastructure. These various strands of engineering were closely tied to one another, with many engineers moving between them, and in a number of cases we see civil engineers filing patents, or mechanical engineers relying on income from civil and consulting work while developing new inventions.

9 Conclusions

This paper documents the emergence of a new division of labor, characterized by the emergence of professional engineers, and by doing so it provides a new perspective

⁵²Between 1750 and 1770, for example, Smeaton was responsible for the Eddystone Lighthouse, the Colstream Bridge, work on the Perth Bridge, the Potteric Carr Drainage, work on the London Bridge Waterworks, and the Adlingfleet Drainage. In just the first decade of the 19th century, John Rennie built the Kelso Bridge, the Leith East Docks, the London Docks, the East India Docks in London, the Humber Dock in Hull, and oversaw the drainage of the Wildmore Fens. Further evidence on this patterns is provided in Appendix Table 50.

on the Industrial Revolution. Central to this perspective is the idea that there was a change in the process through which new technology developed, an innovation in the process of innovation. I am not the first to argue that the innovation process changed in important ways during this period. What is new here is backing that argument up with quantitative evidence and describing in more detail the nature of the change.

Beyond enriching our understanding of one of the most important events in economic history, the patterns I document during the Industrial Revolution can also provide a point of reference as we consider the consequences of more recent fundamental changes in the innovation system, such as the emergence of the research university, the growth of corporate R&D labs, or the potential impact of the use of AI for technology development. Such fundamental changes in the innovation system are difficult to study because they occur rarely, and they are often ignored in growth theories. However, they may have enormous consequences for the rate of technological progress and economic growth.

References

1836. Introduction. *Transactions of the Institutions of Civil Engineers*, **1**.
1928. *A Brief History of the Institution of Civil Engineers*. London: Institution of Civil Engineers.
- Abramitzky, Ran, Boustan, Leah, Eriksson, Katherine, Feigenbaum, James, & Pérez, Santiago. 2021. Automated linking of historical data. *Journal of Economic Literature*, **59**(3), 865–918.
- Acemoglu, Daron, Johnson, Simon, & Robinson, James. 2005. The Rise of Europe: Atlantic Trade, Institutional Change, and Economic Growth. *American Economic Review*, **95**(3), 546 – 579.
- Addis, Bill. 2007. *Building: 3000 Years of Design Engineering and Construction*. London: Phaidon.
- Alder, Ken. 1997. *Engineering the Revolution*. Chicago: University of Chicago Press.
- Allen, Robert C. 2009a. *The British Industrial Revolution in Global Perspective*. Cambridge University Press.
- Allen, Robert C. 2009b. The Industrial Revolution in Miniature: The Spinning Jenny in Britain, France, and India. *The Journal of Economic History*, **69**(4), 901–927.
- Anderson, Michael L. 2008. Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association*, **103**(484), 1481–1495.
- Bailey, Martha J, Cole, Connor, Henderson, Morgan, & Massey, Catherine. 2020. How well do automated linking methods perform? Lessons from US historical data. *Journal of Economic Literature*, **58**(4), 997–1044.
- Benjamini, Yoav, Krieger, Abba M, & Yekutieli, Daniel. 2006. Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, **93**(3), 491–507.
- Billington, Stephen D., & Hanna, Alan J. 2018 (June). *That’s Classified! Inventing a New Patent Taxonomy*. Queens University Center for Economic History Working Paper No. 2018-06.
- Bottomley, Sean. 2014. *The British patent system during the Industrial Revolution 1700–1852: From privilege to property*. Vol. 28. Cambridge University Press.

- Brunt, L, Lerner, J, & Nicholas, T. 2012. Inducement Prizes and Innovation. *Journal of Industrial Economics*, **60**(4), 657–696.
- Burton, M Diane, & Nicholas, Tom. 2017. Prizes, Patents and the Search for Longitude. *Explorations in Economic History*, **64**, 21–36.
- Clapham, J.H. 1964. *An Economic History of Modern Britain*. Cambridge University Press.
- Coryton, John. 1855. *A Treatise on the Law of Letters Patent*. H. Sweet.
- de Pleijt, Alexandra, Nuvolari, Alessandro, & Weisdorf, Jacob. 2020. Human Capital Formation during the Industrial Revolution: Evidence from the use of Steam Engines. *Journal of the European Economics Association*, **18**(2), 829–889.
- Dutton, H.I. 1984. *The Patent System and Inventive Activity During the Industrial Revolution, 1750-1852*. Manchester University Press.
- Fairbairn, William. 1859. *Three Lectures on the Rise and Progress of Civil Engineering and on Popular Education*. Derby: W. and W. Pike.
- Fernihough, Alan, & O'Rourke, Kevin Hjortshøj. 2021. Coal and the European industrial revolution. *The Economic Journal*, **131**(635), 1135–1149.
- Ferrie, Joseph P. 1996. A new sample of males linked from the public use microdata sample of the 1850 US federal census of population to the 1860 US federal census manuscript schedules. *Historical Methods*, **29**(4), 141–156.
- Galor, Oded. 2011. *Unified Growth Theory*. Princeton University Press.
- Galor, Oded, & Weil, David N. 2000. Population, Technology, and Growth: From Malthusian Stagnation to the Demographic Transition and Beyond. *American Economic Review*, **90**(4), 806 – 828.
- Hallmann, Carl, Rosenberger, Lukas, & Yavuz, Emre E. 2021 (Nov.). *Invention and Technological Leadership During the Industrial Revolution*. Working Paper.
- Hanlon, W. Walker. 2015. Necessity is the Mother of Invention: Input Supplies and Directed Technical Change. *Econometrica*, **83**(1), 67–100.
- Hanlon, W. Walker. 2022 (Jan.). *Bridging Science and Technology During the Industrial Revolution*. Working Paper.
- Hansen, Gary D, & Prescott, Edward C. 2002. Malthus to Solow. *American Economic Review*, **92**(4), 1205–1217.

- Howes, Anton. 2017. *The Relevance of Skills to Innovation during the British Industrial Revolution, 1547-1851*. Mimeo.
- Jacob, Margaret C. 2014. *The First Knowledge Economy*. Cambridge University Press.
- Jones, Benjamin F. 2009. The burden of knowledge and the “death of the renaissance man”: Is innovation getting harder? *The Review of Economic Studies*, **76**(1), 283–317.
- Kelly, Morgan, & Ó Gráda, Cormac. 2016. Adam Smith, Watch Prices, and the Industrial Revolution. *Quarterly Journal of Economics*, 1727–1752.
- Kelly, Morgan, & Ó Gráda, Cormac. 2022. Connecting the scientific and Industrial Revolutions: The role of practical mathematics. *The Journal of Economic History*, **82**(3), 841–873.
- Kelly, Morgan, Mokyr, Joel, & Ó Gráda, Cormac. 2014. Precocious Albion: a New interpretation of the British Industrial Revolution. *Annual Review of Economics*, **6**, 363–389.
- Kelly, Morgan, Mokyr, Joel, & Ó Gráda, Cormac. 2023. The Mechanics of the Industrial Revolution. *Journal of Political Economy*, **131**(1), 59–94.
- Khan, B Zorina. 2018. Human Capital, Knowledge and Economic Development: Evidence from the British Industrial Revolution, 1750–1930. *Cliometrica*, **12**(2), 313–341.
- Khan, B Zorina, & Sokoloff, Kenneth L. 1993. “Schemes of practical utility”: entrepreneurship and innovation among “great inventors” in the United States, 1790–1865. *The Journal of Economic History*, **53**(2), 289–307.
- Khan, B Zorina, & Sokoloff, Kenneth L. 2004. Institutions and democratic invention in 19th-century America: evidence from “great inventors,” 1790–1930. *American Economic Review*, **94**(2), 395–401.
- Kugler, Alice. 2023 (Jan.). *The Responsiveness of Inventing: Evidence from a Patent Fee Reform*. Mimeo.
- Landes, David S. 1969. *The Unbound Prometheus*. London: Cambridge University Press.

- Lundgreen, Peter. 1990. Engineering education in Europe and the USA, 1750-1930: The rise to dominance of school culture and the engineering professions. *Annals of science*, **47**(1), 33–75.
- MacLeod, Christine. 1988. *Inventing the Industrial Revolution*. Cambridge, UK: Cambridge University Press.
- MacLeod, Christine, & Nuvolari, Alessandro. 2009. ‘Glorious Times’: The Emergence of Mechanical Engineering in Early Industrial Britain, c. 1700-1850. *Brussels Economic Review - Cahiers Economiques de Bruxelles*, **52**(3/4).
- MacLeod, Christine, Tann, Jennifer, Andrew, James, & Stein, Jeremy. 2003. Evaluating Inventive Activity: The Cost of Nineteenth-Century UK Patents and the Fallibility of Renewal Data. *The Economic History Review*, **56**(3), pp. 537–562.
- Maloney, William F, & Valencia Caicedo, Felipe. 2022. Engineering growth. *Journal of the European Economic Association*, **20**(4), 1554–1594.
- Meisenzahl, Ralf, & Mokyr, Joel. 2012. *The Rate and Direction of Invention in the British Industrial Revolution: Incentives and Institutions*. University of Chicago Press.
- Michaels, Guy, Rauch, Ferdinand, & Redding, Stephen J. 2019. Task Specialization in US Cities from 1880 to 2000. *Journal of the European Economic Association*, **17**(3), 754–798.
- Mokyr, Joel. 2002. *The Gifts of Athena*. Princeton: Princeton University Press.
- Mokyr, Joel. 2004. Accounting for the Industrial Revolution. *Pages 1–27 of: The Cambridge Economic History of Modern Britain*. Cambridge University Press.
- Mokyr, Joel. 2005. *Handbook of Economic Growth*. Amsterdam: Elsevier. Chap. Long-Term Economic Growth and the History of Technology, pages 1113–80.
- Mokyr, Joel. 2009. *The Enlightened Economy*. New Haven: Yale University Press.
- Mokyr, Joel, Sarid, Assaf, & Van Der Beek, Karine. 2022. The Wheels of Change: Technology Adoption, Millwrights and the Persistence in Britain’s Industrialisation. *The Economic Journal*, **132**(645), 1894–1926.
- Moser, P. 2012. Innovation Without Patents: Evidence from World’s Fairs. *Journal of Law and Economics*, **55**(1), pp. 43–74.

- Moser, Petra. 2005. How Do Patent Laws Influence Innovation? Evidence from Nineteenth-Century World's Fairs. *American Economic Review*, **95**(4), 1214.
- Murphy, K.M., Shleifer, A, & Vishny, R.W. 1991. The Allocation of Talent: Implications for Growth. *Quarterly Journal of Economics*, **106**(2), 503–530.
- Nicholas, T. 2011. Cheaper Patents. *Research Policy*, **40**(2), 325–339.
- North, Douglass, & Thomas, Robert Paul. 1973. *The Rise of the Western World*. Cambridge: Cambridge University Press.
- North, Douglass C., & Weingast, Barry R. 1989. Constitutions and Commitment: The Evolution of Institutional Governing Public Choice in Seventeenth-Century England. *The Journal of Economic History*, **49**(4), pp. 803–832.
- Nuvolari, A, & Tartari, V. 2011. Bennet Woodcroft and the Value of English Patents, 1617-1841. *Explorations in Economic History*, **48**, 97–115.
- Nuvolari, Alessandro, Tartari, Valentina, & Tranchero, Matteo. 2021. Patterns of Innovation During the Industrial Revolution: A Reappraisal Using a Composite Indicator of Patent Quality. *Explorations in Economic History*, **82**.
- Nuvolari, Alessandro, Tortorici, Gaspare, & Vasta, Michelangelo. 2023. British-French technology transfer from the Revolution to Louis Philippe (1791–1844): evidence from patent data. *The Journal of Economic History*, **83**(3), 833–873.
- Onions, C.T. (ed). 1966. *The Oxford Dictionary of English Etymology*. Oxford University Press.
- Rees, Abraham. 1819. *The Cyclopaedia*. Longman, Hurst, Rees, Orme & Brown, etc.
- Romer, PM. 1990. Endogenous Technological Change. *Journal of Political Economy*, **98**(5, Part 2), S71–S102.
- Rosenberg, Nathan. 1974. Science, Invention and Economic Growth. *The Economic Journal*, **84**(333), 90–108.
- Skempton, A.W. 1996. *Civil Engineers and Engineering in Britain, 1600-1830*. Aldershot, Hampshire: Variorum.
- Skempton, AW, Chrimes, MM, Cox, RC, Cross-Rudkin, PSM, Reinnison, RW, & Ruddock, EC (eds). 2002. *A Biographical Dictionary of Civil Engineers in Great Britain and Ireland*. Vol. 1: 1500-1830. Thomas Telford.

- Squicciarini, Mara P, & Voigtländer, Nico. 2015. Human Capital and Industrialization: Evidence from the Age of Enlightenment. *The Quarterly Journal of Economics*, **130**(4), 1825–1883.
- Sullivan, Richard J. 1989. England’s “Age of Invention”: The acceleration of patents and patentable invention during the Industrial Revolution. *Explorations in Economic History*, **26**(4), 424–452.
- Sullivan, Richard J. 1990. The revolution of ideas: widespread patenting and invention during the English industrial revolution. *The Journal of Economic History*, **50**(2), 349–362.
- Watson, Garth. 1989. *The Smeatonians. The Society of Civil Engineers*. Thomas Telford.
- Whitehead, Alfred North. 1925. *Science and the Modern World*. London: The Free Press.
- Woodcroft, Bennet. 1854a. *Subject Matter Index of Patents of Invention*. Queen’s Printing Office.
- Woodcroft, Bennett. 1854b. *Titles of Patents of Invention, Chronologically Arranged*. George Edward Eyre and William Spottiswoode.

Appendix

Appendix Table of Contents

	Page
A. Theory appendix	55
B. Evidence from Google Ngrams	68
C. Verb stem analysis appendix	69
D. British patent data appendix	75
E. British patent analysis appendix	88
F. Results linking patents to scientific articles	116
G. Evidence on the licensing and sale of patents	119
H. Analyzing inventor's backgrounds	120
I. French patent analysis appendix	123
J. Civil engineering appendix	127
K. Government and the engineering profession	131

A Theory Appendix

This section presents the details of the theory that embeds the emergence of a group of professional inventors into a model of endogenous growth. The model builds on elements from Romer (1990) as well as Unified Growth Theory (Galor & Weil, 2000; Galor, 2011). The goal is to show how the arrival of a group of professional inventors, engineers, can act as a mechanism through which the economy transitions from a slow “pre-modern” growth into more rapid “modern” economic growth regime, as well as to connect my analysis to existing work on the factors that contributed to the onset of the Industrial Revolution.

A.0.1 Demand

The model is written in continuous-time and, for simplicity, time subscripts are suppressed when possible. The population of the economy is fixed at 1. There is a homogeneous final good with a price normalized to $P=1$. The model admits an infinitely lived representative consumer with CRRA preferences over consumption of the final good:

$$\int_0^{\infty} \frac{C^{1-\sigma} - 1}{1-\sigma} e^{-\rho t} dt, \quad (1)$$

where σ is the coefficient of relative risk aversion and ρ is the time preference parameter. The budget constraint is given by, $C + I + F \leq Y$ where Y is total output of final goods, I is the amount of final goods used in the production of machinery, and F is a fixed cost associated with undertaking research.

A.0.2 Production of final goods

Final goods are produced using skilled labor H , unskilled labor L , and machines, in a perfectly competitive market with a constant returns to scale technology. The aggregate production function is,

$$Y = \frac{1}{1-\beta} \left(\int_0^N x(j)^{1-\beta} dj \right) [(\iota H)^\alpha + L^\alpha]^{\frac{\beta}{\alpha}} \quad (2)$$

where N is the level of technology (number of machine designs available), $x(j)$ is the quantity of machine type j used in production, $\alpha \in (-\infty, 1)$ and $\beta \in (0, 1)$ are production function parameters, and $\iota \in (0, 1)$ is the fraction of high-skilled workers' time left over for productive activities after they undertake the education necessary to become skilled (so $1 - \iota$ reflects the cost, in terms of time, of acquiring skill). Final goods producers solve a standard optimization problem taking as given the wage for low-skilled workers (w_L), wages for high-skilled workers (w_H), and a price $\chi(j)$ for machines of type j . The first order conditions are,

$$w_L = \frac{\beta}{1 - \beta} \left(\int_0^N x(j)^{1-\beta} dj \right) [(\iota H)^\alpha + L^\alpha]^{\frac{\beta-\alpha}{\alpha}} L^{\alpha-1} \quad (3)$$

$$w_H = \frac{\beta}{1 - \beta} \left(\int_0^N x(j)^{1-\beta} dj \right) [(\iota H)^\alpha + L^\alpha]^{\frac{\beta-\alpha}{\alpha}} \iota^{\alpha-1} H^{\alpha-1} \quad (4)$$

$$x(j) = \chi(j)^{\frac{-1}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}} \quad (5)$$

A.0.3 Machine producers

Machine producers hold a perpetual monopoly over their machine design, which they produce using final goods. Machines depreciate fully after use. Setting aside for now the cost of obtaining a machine design, the profits of machine makers are given by $\pi(j) = (\chi(j) - \phi)x(j)$ where ϕ reflects the cost of producing a new machine in terms of output used. Using the first order conditions from the final goods producers' problem together with the first order condition for the machine makers' optimization problem gives $\chi(j) = \frac{\phi}{1-\beta}$. Thus, the machine price is just a constant mark-up over the marginal cost. Using this, we can rewrite the machine makers' profits as,

$$\pi(j) = \beta \left(\frac{1 - \beta}{\phi} \right)^{\frac{1-\beta}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}} \quad (6)$$

It is useful to note here that profits are independent of the technology level. However, profit does depend on the number of high and low-skilled workers active in producing final goods.

A.0.4 Occupation choice and technology development

Individuals are endowed with one unit of time and must choose discretely to either become a low-skilled worker or to invest in skills and then become either a high-skilled worker or a professional researcher. Skills depreciate completely each period. Let E denote the quantity of professional researchers (engineers), so $L + H + E = 1$. Low skilled workers earn w_L while high-skilled workers earn ιw_H (since they have to devote a fraction $1 - \iota$ of their time to becoming skilled). Professional researchers, who also must spend a fraction $1 - \iota$ of their time to become skilled, allocate the remainder of their time to producing new inventions.

New technologies arise from two sources. First, new technologies may be developed by professional researchers (engineers). Since these researchers must have skills, the total time available for research is ιE . In addition, they must pay some fixed cost f to undertake research. Each professional researcher then produces a new machine design with a probability ηN . This productivity scales with N , a standard feature of endogenous growth models following Romer (1990). This reflects the idea that professional researchers are more likely to generate a new technology if they have more existing ideas and tools to work with. As (Romer, 1990) explains, “The engineer working today is more productive because he or she can take advantage of all the additional knowledge accumulated as design problems were solved...” The overall number of new technologies generated by the professional research sector within a period is then $\eta N \iota E$.

In addition, new technologies may be developed by high-skilled workers as a serendipitous by-product of production.⁵³ This occurs for each high-skilled worker with probability γN . It is useful to note that making the probability of a serendipitous discovery increasing in N is not a vital assumption for the model, but it is useful for helping the model match the patterns observed in the data.⁵⁴ Given this

⁵³The assumption that only high-skilled workers and not low-skilled workers generate new inventions as a by-product of production is not critical for the main results of the theory, but it seems more reasonable to confine the development of new technologies to only those with skills.

⁵⁴Specifically, if instead the rate of serendipitous discoveries occurred at rate γ rather than γN , then the growth rate of technologies generated through this channel is declining over time. That does not match the patterns in the patent data, which show that innovations by non-engineers grew at a constant (but low) rate during my study period.

formulation, the number of new technologies generated through this channel is $\gamma N \iota H$.

Motivated by the results presented in my empirical analysis, I make the following key assumption:

Assumption: $\eta > \gamma$, so professional researchers are more productive at generating new technologies than high-skilled workers engaged mainly in goods production.

Technological change in the economy is $\dot{N} = \gamma N \iota H + \eta N \iota E$ and the rate of change is,

$$\frac{\dot{N}}{N} = \gamma \iota H + \eta \iota E \quad (7)$$

The discounted present value of a new machine design depends on the profits of machine makers according to $V = (\pi + \dot{V})/r$, where r is the interest rate and \dot{V} accounts for changes in future profits.⁵⁵

When a professional researcher develops a new technology, their ability to capture the rents from their design depends on the strength of intellectual property protection. The strength of IP protection is represented by the parameter $\lambda \in (0, 1)$ which reflects the probability that an inventor retains ownership over a design. If they retain ownership, then they sell of the design to one out of a large group of potential machine making firms, thus capturing the full discounted present value of the invention. If they do not, I assume that the design is appropriated by the government which sells the design for the full value and then distributes the proceeds to all individuals in the economy through equal lump-sum payments. For simplicity, I assume that when high-skilled workers generate serendipitous inventions they are not able to monetize the value. Instead, the invention is appropriated by the government, auctioned off to a machine firm, and the value is returned to individuals through lump-sum transfers. This is not a critical assumption. It is made only because it simplifies the exposition

⁵⁵It is worth noting that $\dot{V} \leq 0$ in this model. To see this, note that profits depend only on the amount of skilled and unskilled workers employed in final goods production. As shown below, for low levels of N all workers will be used in final goods production, and this amount will fall if at some point some workers begin choosing to become researchers. Thus, profits can only fall over time in the model.

of the model and helps emphasize the fact that growth during the pre-modern period is not dependent on the availability of intellectual property protection.

The expected return to low-skilled workers, high-skilled workers, and researchers, respectively, is,

$$ER_L = w_L = \beta(1 - \beta)^{\frac{1-2\beta}{\beta}} \phi^{\frac{\beta-1}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}} L^{\alpha-1} N \quad (8)$$

$$ER_H = \iota w_H = \beta(1 - \beta)^{\frac{1-2\beta}{\beta}} \phi^{\frac{\beta-1}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}} \iota^\alpha H^{\alpha-1} N \quad (9)$$

$$ER_E = \iota \lambda \eta V N - f = \frac{\iota \lambda \eta \beta}{r} \left(\frac{1 - \beta}{\phi} \right)^{\frac{1-\beta}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}} N + \frac{\iota \lambda \eta \dot{V}}{r} N - f \quad (10)$$

I assume that professional researchers are able to insure each other against the risk of not producing an invention in any particular period, so that in choosing an occupation they care only about the expected returns.

In equilibrium, individuals will choose between being a low-skilled worker, a high-skilled worker, or a researcher, to maximize their expected return. Since both high and low-skilled workers are vital to the production of final goods (since $\alpha < 1$), we know that there will be positive quantities of both of these types of workers. This implies that in equilibrium $ER_H = ER_L$. Using this and Eqs. 8 and 9 we can solve for the equilibrium relationship between L and H . This is $H/L = \iota^{\frac{\alpha}{1-\alpha}}$. This equation tells us that when high and low-skilled workers are substitutes ($\alpha > 0$) the share of high-skilled workers in the economy will increase when the costs of becoming skilled falls (higher ι). Otherwise, if $\alpha < 0$, the share of high-skilled workers will fall as the cost of obtaining skill falls. The relevant case for our setting is likely to be $\alpha > 0$, so that locations where it is easier to acquire skills also have more skilled workers.

One feature in Eq. 10 that is worth noting is that the ι parameter increases the returns to being a professional researcher in two ways. First, there is a direct effect on engineers through easier access to skills. Second, easier access to skills raises the return to being a researcher by increasing the number of skilled workers in the economy able to work with the new technologies that professional researchers discover. This

channel, represented by the ιH term, reflects another connection between the theory and the empirical setting, where historical evidence suggests that the availability of skilled craftsmen in England who could construct new machines played an important role in incentivizing the development of those technologies.⁵⁶

A.0.5 Development path and key results

Consider the development path of the economy starting from a very low initial technology level. The first useful prediction of the theory is that the professional research sector will be inoperative when the technology level is sufficiently low.

Prop. 1: There exists some \underline{N} such that for all $N < \underline{N}$, $ER_E < ER_H = ER_L$ when $E = 0$ and therefore no individuals choose to become professional researchers.

Proof of Prop. 1: This follows directly from the fact that ER_E , ER_H and ER_L are continuous functions of N and that $\lim_{N \rightarrow 0} ER_E < 0$ while $\lim_{N \rightarrow 0} ER_H = 0$.

The intuition here is simple. Since the productivity of researchers scales with N , at low levels of N they are unproductive, and so it does not pay to become a professional researcher given the fixed costs involved.

Starting from an initially low level of N , Proposition 1 tells us that the economy will initially be one in which there are no professional researchers. This initial “pre-modern” period is characterized by relatively slow growth, which may be very slow if γ is low, and no professional research sector. This pre-modern period may potentially last for a very long time; under certain conditions the economy may be stuck in pre-modern growth forever, as explained shortly. In periods characterized by pre-modern growth (where $E = 0$), we have the following equilibrium allocations of high and low skilled workers,

$$\tilde{H} = \frac{1}{1 + \iota^{\frac{-\alpha}{1-\alpha}}} \quad \tilde{L} = \frac{\iota^{\frac{-\alpha}{1-\alpha}}}{1 + \iota^{\frac{-\alpha}{1-\alpha}}}$$

derived by using the conditions $ER_L = ER_H$ and $H + L = 1$.

⁵⁶See Mokyr (2009), Chapter 6.

It is important to note that during pre-modern growth, technological progress is not dependent on the availability of intellectual property protection, so the model can capture historical periods in which new technologies were developed even though inventors received little or no monetary reward from their discoveries.

Next, I show that when the professional research sector is operating, the growth rate increases.

Prop. 2: When $\eta > \gamma$, the growth rate is increasing in E .

Proof of Prop. 2: *The growth rate $g = \dot{N}/N = (\gamma\iota H + \eta\iota E)$. Using $H + L + E = 1$ and substituting in $L = H\iota^{\frac{-\alpha}{1-\alpha}}$, we have $H = (1 - E)/(1 + \iota^{\frac{-\alpha}{1-\alpha}})$. Thus,*

$$\frac{\dot{N}}{N} = \frac{\gamma\iota}{1 + \iota^{\frac{-\alpha}{1-\alpha}}} + E \left(\eta\iota - \frac{\gamma\iota}{1 + \iota^{\frac{-\alpha}{1-\alpha}}} \right)$$

which is increasing in E when $\eta > \gamma$.

The growth rate in the proof above has an intuitive structure. The first term is the rate of growth in the pre-modern period, while the second term is the product of the share of professional researchers in the economy and the difference between the rate at which they produce inventions ($\eta\iota$) and the rate of serendipitous discovery by high-skilled manufacturing workers ($\gamma\iota$), accounting for the fact that only a fraction of non-researchers end up becoming high-skilled (reflected in the $1 + \iota^{\frac{-\alpha}{1-\alpha}}$ term).

The next proposition describes the conditions under which the economy will eventually transition into modern growth. It is useful to begin by defining the following key condition:

Condition 1: $(1 - \beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1 + \iota^{\frac{-\alpha}{1-\alpha}}) > \rho$

Prop. 3: If Condition 1 holds, there exists some \bar{N} such that for any $N > \bar{N}$, $ER_E > ER_H = ER_L$ when $E = 0$ and therefore at least some individuals choose to become researchers. If Condition 1 fails, then there is no N such that $ER_E > ER_H = ER_L$ when $E = 0$ and the professional research sector never emerges.

Proof of Proposition 3: *To prove the first statement, by contradiction, suppose that $(1 - \beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1 + \iota^{\frac{-\alpha}{1-\alpha}}) > \rho$ but that $ER_L > ER_E$ for all N . This implies*

that $\lim_{N \rightarrow +\infty} ER_L - ER_E \geq 0$. Since there is no professional research sector, the economy will be in a balanced growth path characterized by $E = 0$, $H = \frac{1}{1 + \iota^{\frac{-\alpha}{1-\alpha}}}$,

$$L = \frac{\iota^{\frac{-\alpha}{1-\alpha}}}{1 + \iota^{\frac{-\alpha}{1-\alpha}}}, \text{ and } \dot{V} = 0.$$

Thus,

$$\lim_{N \rightarrow +\infty} N \left[\beta(1-\beta)^{\frac{1-2\beta}{\beta}} \phi^{\frac{\beta-1}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}} L^{\alpha-1} - \frac{\iota \lambda \eta \beta}{r} \left(\frac{1-\beta}{\phi} \right)^{\frac{1-\beta}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}} + \frac{f}{N} \right] \geq 0$$

This is true only if,

$$\beta(1-\beta)^{\frac{1-2\beta}{\beta}} \phi^{\frac{\beta-1}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}} L^{\alpha-1} \geq \frac{\iota \lambda \eta \beta}{r} \left(\frac{1-\beta}{\phi} \right)^{\frac{1-\beta}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}}$$

Substituting in for L and H and solving gives, $r \geq (1-\beta)\lambda\eta\iota$.

We now need to substitute in for r using the intertemporal optimization condition. Since the professional research sector does not operate in this scenario, the steady state growth rate is $\dot{N}/N = \gamma\iota H = \gamma\iota/(1 + \iota^{\frac{-\alpha}{1-\alpha}})$. The intertemporal optimization condition implies that $(r - \rho)/\sigma = \gamma\iota/(1 + \iota^{\frac{-\alpha}{1-\alpha}})$. Solving for r and substituting in we have,

$$\rho \geq (1-\beta)\lambda\eta\iota - \frac{\gamma\iota\sigma}{(1 + \iota^{\frac{-\alpha}{1-\alpha}})}$$

But this contradicts the initial assumption.

To prove the second statement, given Proposition 1, it is sufficient to show that $(1-\beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1 + \iota^{\frac{-\alpha}{1-\alpha}}) < \rho$ implies $d(ER_E - ER_L)/dN < 0$ for any N .

$$\frac{d(ER_E - ER_L)}{dN} = \frac{\iota \lambda \eta \beta}{r} \left(\frac{1-\beta}{\phi} \right)^{\frac{1-\beta}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}} + \frac{\iota \lambda \eta \dot{V}}{r} - \beta(1-\beta)^{\frac{1-2\beta}{\beta}} \phi^{\frac{\beta-1}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}} L^{\alpha-1}$$

Since $\dot{V} \leq 0$, for $d(ER_E - ER_L)/dN < 0$ it is sufficient that,

$$\frac{\iota \lambda \eta \beta}{r} \left(\frac{1-\beta}{\phi} \right)^{\frac{1-\beta}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}} - \beta(1-\beta)^{\frac{1-2\beta}{\beta}} \phi^{\frac{\beta-1}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}} L^{\alpha-1} < 0$$

Reorganizing and substituting in for L and H , we have,

$$(1 - \beta)\iota\lambda\eta < r$$

Thus, whenever this condition holds, $d(ER_E - ER_L)/dN < 0$. It remains to show that this must hold under the initial assumption of $(1 - \beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1 + \iota^{\frac{-\alpha}{1-\alpha}}) < \rho$. This can be reorganized to obtain $(1 - \beta)\lambda\eta\iota < \rho + (\gamma\iota\sigma)/(1 + \iota^{\frac{-\alpha}{1-\alpha}})$. Thus, a sufficient condition for $(1 - \beta)\iota\lambda\eta < r$ is $\rho + (\gamma\iota\sigma)/(1 + \iota^{\frac{-\alpha}{1-\alpha}}) \leq r$. This can be reorganized to,

$$\frac{\gamma\iota}{(1 + \iota^{\frac{-\alpha}{1-\alpha}})} \leq \frac{r - \rho}{\sigma}$$

To see that this must be true, note that the intertemporal optimization condition requires that $(r - \rho)/\sigma = g$ where g is the growth rate of the economy, and that $g \geq \gamma\iota/(1 + \iota^{\frac{-\alpha}{1-\alpha}})$ (see Proposition 3). Thus, if $(1 - \beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1 + \iota^{\frac{-\alpha}{1-\alpha}}) < \rho$ it can never be the case that $ER_E > ER_L$ with $E = 0$ and so the professional research sector can never begin operating.

The intuition here is that, under Condition 1, the return to professional researchers increases more rapidly with N than returns in the production sector (when $E = 0$). As a result, eventually the return to becoming a researcher exceeds the wage of production workers and some individuals have an incentive to become professional researchers.⁵⁷

Proposition 3 is a central result of the theory. It tells us that the professional research sector emerges only under certain conditions. In particular, the emergence of the professional research sector depends crucially on the availability of institutions that allow inventors to monetize their inventions, reflected in the λ parameter. Whether a professional research sector emerges also depends on the ease with which individuals can acquire skills, reflected in the ι parameter (note that the left-hand

⁵⁷This begs the question of why the return to the research sector does not continue to rise faster than wages in the production sector after the research sector begins to operate. The reason that this does not happen is that as fewer individuals choose to become workers, the profits of the machine making firms fall (see Eq. 6) pulling down the value of new inventions and thus the returns to becoming a professional researcher.

side of Condition 1 is increasing in ι). Only when these conditions are satisfied will a professional research sector eventually emerge, allowing growth to accelerate. Thus, Proposition 3 connects the model to the features of the historical setting, specifically the availability of useful knowledge, a culture of learning, access to training in craft skills (such as through apprenticeships), and institutions that allowed inventors to monetize inventions.

Once modern economic growth begins, the economy approaches a new long-run balanced growth path. On the equilibrium balanced growth path, $ER_L = ER_H = ER_E$, $\dot{V} = 0$, and as $N \rightarrow +\infty$ the economy approaches fixed shares of researchers, skilled, and unskilled workers.⁵⁸ The long-run ratio of researchers to production workers in the economy is,

$$\theta = \frac{E}{H + L} = (1 - \beta)\lambda\eta\iota - \frac{\gamma\sigma\iota^{\frac{1}{1-\alpha}}}{1 + \iota^{\frac{\alpha}{1-\alpha}}} - \rho \quad (11)$$

This share is increasing in the productivity of researchers η , as we would expect, as well as the importance of machines in the production function $(1 - \beta)$ and the strength of IP protection represented by λ . The share is decreasing in the rate at which high-skilled manufacturing workers generate new technologies (γ), decreasing in the time discount factor ρ , and decreasing in the coefficient of relative risk aversion σ . This is intuitive given that the value of research is mainly realized in the future.

As indicated by Proposition 2, the long-run growth rate in the modern economy with an active professional research sector is faster than the rate experienced in the pre-modern period. Thus, the emergence of professional researchers has pushed the economy onto a more rapid growth path. How much growth increases depends on the difference between η and γ .

Finally, it is useful to show that the model provides additional predictions that are consistent with the historical record:

Prop. 4: When Condition 1 holds, the economy converges to a long-run balanced growth path in which the share of skilled workers in the economy is higher than the share during the pre-modern growth period.

⁵⁸Note that the no-Ponzi game condition requires that $(1 - \sigma)g < \rho$, which restricts the admissible set of parameter values.

Proof of Proposition 4: To prove this proposition it is sufficient to show that, under Condition 1, $\tilde{L} > L^*$, where $\tilde{L} = 1 / \left(1 + \iota^{\frac{\alpha}{1-\alpha}}\right)$ is the amount of low-skilled workers in the pre-modern period and L^* is given by Eq. 12. It will be the case that $\tilde{L} > L^*$ when,

$$\frac{1}{1 + \iota^{\frac{\alpha}{1-\alpha}}} > \frac{\eta\sigma\iota + \rho}{(1 - \beta)\lambda\eta\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} + \eta\sigma\iota(1 + \iota^{\frac{\alpha}{1-\alpha}})}$$

$$(1 - \beta)\lambda\eta\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} + \eta\sigma\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) > \eta\sigma\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) + \rho(1 + \iota^{\frac{\alpha}{1-\alpha}})$$

$$(1 - \beta)\lambda\eta\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} > \rho(1 + \iota^{\frac{\alpha}{1-\alpha}})$$

$$(1 - \beta)\lambda\eta\iota - \frac{\gamma\sigma\iota^{\frac{1}{1-\alpha}}}{(1 + \iota^{\frac{\alpha}{1-\alpha}})} > \rho$$

$$(1 - \beta)\lambda\eta\iota - \frac{\gamma\sigma\iota}{(1 + \iota^{\frac{\alpha}{1-\alpha}})} > \rho$$

This is exactly Condition 1.

Thus, the onset of modern economic growth is characterized not just by an accelerated rate of technological progress but also by an increase in the share of skilled individuals in the economy.⁵⁹

A.0.6 Long-run balanced growth path

Once modern economic growth begins (if it does), the economy begins to approach a new long-run steady state characterized by a fixed proportion of high-skilled workers, low-skilled workers, and professional researchers. In equilibrium, $ER_L = ER_E$, so,

⁵⁹It is worth noting that this increase is driven by the demand for skilled workers in the professional research sector. The ratio of skilled to unskilled production workers is unchanged.

$$\beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}[(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1}N = \frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}[(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}}N + \frac{\iota\lambda\eta\dot{V}}{r}N - f$$

On the balanced growth path, $\dot{V} = 0$ and so as $N \rightarrow +\infty$ the economy approaches,

$$\beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}[(\iota H)^\alpha + L^\alpha]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1} = \frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}[(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}}$$

This together with $H = \iota^{\frac{\alpha}{1-\alpha}}L$ can be used to show,

$$L = \frac{r\iota^{-1}}{(1-\beta)\lambda\eta(1 + \iota^{\frac{\alpha}{1-\alpha}})}$$

$$H = \frac{r\iota^{\frac{\alpha}{1-\alpha}-1}}{(1-\beta)\lambda\eta(1 + \iota^{\frac{\alpha}{1-\alpha}})}$$

$$E = 1 - \frac{r\iota^{-1}}{(1-\beta)\lambda\eta}$$

The standard intertemporal optimization condition implies that $(r - \rho)/\sigma = g = \gamma\iota H + \eta E$. Substituting for H and E and solving for r, we have,

$$r = \frac{(1-\beta)\lambda\eta(1 + \iota^{\frac{\alpha}{1-\alpha}})(\eta\iota\sigma + \rho)}{(1-\beta)\lambda\eta(1 + \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\iota^{\frac{\alpha}{1-\alpha}}\sigma + \eta\sigma(1 + \iota^{\frac{\alpha}{1-\alpha}})}$$

Substituting this back in, we have,

$$L^* = \frac{\eta\iota\sigma + \rho}{(1-\beta)\lambda\eta\iota(1 - \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} + \eta\sigma\iota(1 + \iota^{\frac{\alpha}{1-\alpha}})} \quad (12)$$

$$H^* = \frac{\iota^{\frac{\alpha}{1-\alpha}}(\eta\iota\sigma + \rho)}{(1-\beta)\lambda\eta\iota(1 - \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} + \eta\sigma\iota(1 + \iota^{\frac{\alpha}{1-\alpha}})} \quad (13)$$

$$E^* = \frac{(1 - \beta)\lambda\eta\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} - \rho(1 + \iota^{\frac{\alpha}{1-\alpha}})}{(1 - \beta)\lambda\eta\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} + \eta\sigma\iota(1 + \iota^{\frac{\alpha}{1-\alpha}})} \quad (14)$$

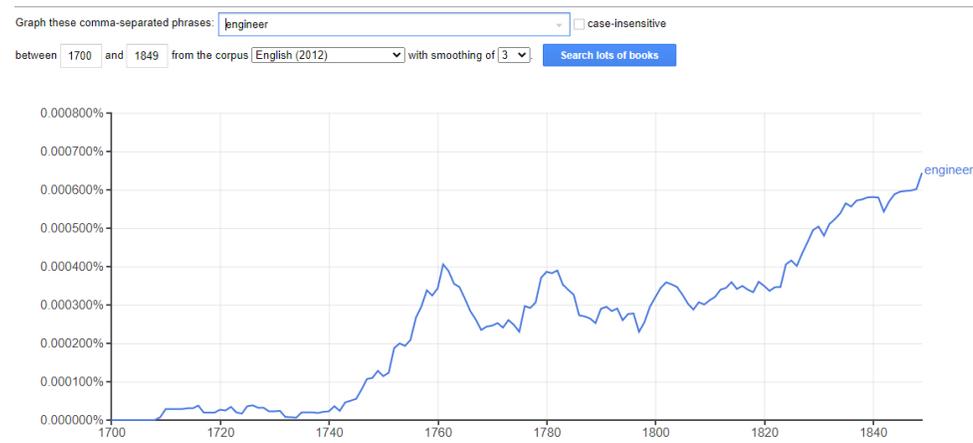
The growth rate is,

$$g = \frac{\gamma\iota}{1 + \iota^{\frac{-\alpha}{1-\alpha}}} + E\left(\eta\iota - \frac{\gamma\iota}{1 + \iota^{\frac{-\alpha}{1-\alpha}}}\right)$$

Here, the first term is the growth rate of the economy when there are no professional researchers, and the second term is the share of professional researchers in the economy multiplied by the difference between the rate at which professional researchers produce innovations and the rate at which high-skilled workers produce innovations, scaled by $1 + \iota^{\frac{-\alpha}{1-\alpha}}$ to reflect the fact that if the share of professional researchers falls there is a less-than-proportional increase in the share of high-skilled workers in the economy.

B Evidence from Google Ngrams

Figure 5 describes the usage of the term “engineer” in books contained in the Google Books repository, as reported by Google Ngrams (<https://books.google.com/ngrams>), from 1700-1850.



Data from Google Ngrams, June 18, 2020.

Figure 5: Google Ngram for “engineer”

C Verb stem analysis appendix

This appendix describes in more detail a text analysis exercise that aims to identify the functional activities that characterized the early engineering profession. In the text, I describe two different approaches to this problem. The first approach, described in Section 2.3, uses verb stems and a LASSO approach to predict who is an engineer based on individuals' ODNB biographies. The second way that I use verb stems, in Section 3, is to identify those activities that are most associated with individuals who describe themselves as engineers. Since these are slightly different problems, I use different approaches, which I describe below. However, they both begin with the same building blocks, which I describe first.

C.1 Extracting verb stems from biographies

The starting point for this analysis is biographical data from the ODNB, a rich data source that has been used in numerous previous studies.⁶⁰ These biographies cover only a select sample of the most successful or notable individuals, so an analysis of this data will not be representative of all engineers. However, it will reflect the activities of upper-tail individuals, the group most likely to invent valuable new technologies and therefore a primary interest of this paper.

I begin by collecting the text of the biographies of all those classified by the ODNB as engineers born before 1850 (439 in total), as well as two natural comparison groups: manufacturers (349 biographies) and those non-engineers classified as involved in science or technology (1547 biographies).⁶¹ Using natural language processing methods, I parse the biographies and identify all verb stems. These verb stems reflect the types of activities that individuals undertook during their lifetime. This procedure identifies 924 verb stems.

⁶⁰Previous studies using these data include Allen (2009a), Meisenzahl & Mokyr (2012), Nuvolari & Tartari (2011), and Khan (2018).

⁶¹Within the ODNB, these are the two natural comparison groups. Most engineers were classified as part of those involved in science and technology, so it is natural to compare to that group. Manufacturers were the other major group of inventors during the study period, as the patent data will show. I exclude military engineers from the engineers group. I also include iron masters as manufacturers. Of those individuals classified as working in science or technology, I do not include manufacturers, artists/engravers, alchemists, or fossil collectors.

C.2 Predicting engineers using verb stems

The first way that I use the verb stems obtained from the ODNB biographies is as part of a task-based approach to predicting who should qualify as an engineer. In this approach, I begin with a training sample of all individuals born after 1825 and apply LASSO regressions to predict whether an individual was an engineer (as identified by historians) based on the verb stems that appear in their biography.

To reduce the scope of the problem, I begin by dropping any verb stem that appears in fewer than 20 biographies. This leaves me with 921 verb stems. To ensure that the results are not driven by the verbs engineer or invent, I drop these verb stems when generating my predictions. I am interested in running regressions of the following form on the training sample of individuals born after 1825:

$$ENG_i = \alpha + VERB_i\Lambda + \epsilon_i$$

where ENG_i is an indicator for whether someone was classified as an engineer in the ODNB and $VERB_i$ is the number of times each verb appears in individual i 's biography. Since there are a large number of explanatory variables in this regression relative to the number of observations in the training sample (543), I apply a LASSO regression methodology to reduce the set of explanatory variables. Finally, I use the estimated $\hat{\Lambda}$ to generate out-of-sample predictions of the likelihood that individuals born before 1825 are engineers, based on the set of verbs appearing in their ODNB biographies.

Table 8 presents the ten individuals with the highest predicted engineer score ($EN\hat{G}_i$) outside of the training sample, together with their ODNB classification and the score. Note that since these are out-of-training-sample predicted values, the score can be greater than one. This list contains some of the most prominent engineers of the late 18th and early 19th centuries. Thomas Telford, John Smeaton, and Isambard Kingdom Brunel, for example, were three of the most important civil engineers of this period, George Stephenson was a pioneering railroad engineer, and Richard Trevethick was a major steam engine engineer. Nine out of the ten individuals on this list were classified by ODNB historians as engineers, the only exception being Thomas Scragg,

a drainpipe machine manufacturer.

Name	ODNB classification	Score
Josiah Parkes	Engineer	5.370907
Thomas Telford	Engineer	3.708711
John Smeaton	Engineer	2.978736
Thomas Scragg	Manufacturer	2.002912
Isambard Kingdom Brunel	Engineer	1.985543
Rowland Mason Ordish	Engineer	1.865937
Richard Trevithick	Engineer	1.836426
John Frederic La Trobe Bateman	Engineer	1.823967
James Meadows Rendel	Engineer	1.818381
George Stephenson	Engineer	1.761452

Table 8: Top predicted engineers

C.3 Using verb stems to define engineers

This subsection describes how I use verb stems to define engineers, as discussed in Section 3 in the main text. For this analysis, I focus on the 338 verbs that appear in at least 100 out of the 2335 biographies used in the analysis. To provide a point of comparison, I begin by identifying a set of ‘neutral’ verbs (e.g., is, do, died, sat, etc.) that are unlikely to reflect activities associated with a particular occupation. I then run the following regression specification:

$$VERB_{vi} = \sum_{v \in \tilde{V}} (\gamma_v ENG_i \theta_v) + \phi_i + \eta_v + \epsilon_{vi}$$

where $VERB_{vi}$ is an indicator for whether verb stem v shows up the biography of individual i , ϕ_i is a set of individual biography fixed effects, which accounts for variation in the length of individual biographies, and η_v is a set of verb fixed effects, to account for variation in the baseline frequency with which each verb is used. The explanatory variables of interest in this regression are constructed by interacting an indicator for whether an individual is an engineer (ENG_i), with θ_v , an indicator variable for each verb in the set of verbs \tilde{V} that excludes neutral verbs. The estimated coefficient for each verb in this set, γ_v , reflects the extent to which that verb is

particularly common in engineer biographies. Since I am looking at many outcomes, I adjust for multiple hypothesis testing by calculating sharpened p-values, following Benjamini *et al.* (2006) and Anderson (2008).

Table 9 presents the top-20 verbs related to engineers from four alternative estimation approaches, but always using the ODNB categorizations to identify engineers. The results in the first two columns correspond to my preferred approach. That approach uses an indicator for whether a verb appears in a biography as the outcome variable and compares engineers to both manufacturers and non-engineers involved in science and technology. The next two columns compare engineers only to manufacturers, followed by two columns comparing them only to those involved in science and technology. While these two sets of results are similar, we can see some interesting contrasts. For example, relative to manufacturers, engineers were more likely to be engaged in activities such as publishing and writing. This is not true when comparing engineers to non-engineers involved in science and technology. Similarly, engineers were more likely to be involved in activities such as manufacturing or supervising when compared to non-engineers involved in science or technology, but not when compared to manufacturers. However, when comparing engineers to either of these groups, I consistently find that engineers are closely associated with activities such as designing, consulting, constructing, and surveying (“invent” and “patent” also have p-values below 0.05 when compared to either group, though they fall outside of the top 20 terms in some cases). The last two columns present results where the count of verbs in a biography is used in place of an indicator for whether a verb appears. This alternative approach delivers very similar results.

It is also interesting to look at whether the activities that define engineers (as identified by ODNB historians) remained relatively constant over time. Table 10 looks at this. The results on the left are based on the biographies for individuals born before 1800 while those on the right are for individuals born in 1800 or later. We can see that, while there are some differences, the set of activities that defines engineers remains quite stable across these two periods. Most importantly, key activities such as design, build, construct, and patent, appear to be central features of the engineering profession across both periods.

It is also useful to look at whether these results depend on whether engineers

Baseline		Compare to manufacturers only		Compare to sci/tech only		Using verb counts as outcome	
Verb stem	Sharpened p-value	Verb stem	Sharpened p-value	Verb stem	Sharpened p-value	Verb stem	Sharpened p-value
design	0.001	design	0.001	design	0.001	design	0.001
build	0.001	construct	0.001	build	0.001	build	0.001
construct	0.001	consult	0.001	construct	0.001	construct	0.001
consult	0.001	complete	0.001	employ	0.001	consult	0.001
patent	0.001	publish	0.001	consult	0.001	employ	0.001
employ	0.001	survey	0.001	patent	0.001	patent	0.001
report	0.001	report	0.001	open	0.001	report	0.001
erect	0.001	propose	0.001	erect	0.001	erect	0.001
survey	0.001	award	0.001	manufacture	0.001	improve	0.001
drive	0.001	advise	0.001	report	0.001	complete	0.001
complete	0.001	assist	0.001	supply	0.001	drive	0.001
open	0.001	connect	0.001	drive	0.001	supervise	0.001
supervise	0.001	test	0.001	improve	0.001	open	0.001
improve	0.001	consider	0.001	supervise	0.001	lay	0.001
lay	0.001	engage	0.001	survey	0.001	propose	0.001
advise	0.001	undertake	0.001	install	0.001	survey	0.001
supply	0.001	act	0.001	lay	0.001	connect	0.001
connect	0.001	prepare	0.001	operate	0.001	supply	0.001
propose	0.001	supervise	0.001	replace	0.001	advise	0.001
invent	0.001	lay	0.001	complete	0.001	act	0.001

Table 9: Verb stem results using alternative comparison groups or outcome variables

Estimated coefficients and t-statistics based on robust standard errors. Sharpened p-values are calculated using the approach from Anderson (2008). Regressions include verb and individual fixed effects. In the first and last set of results, N=789,230. When comparing only to manufacturers, N=266,344. When comparing only to non-engineers working in science or technology, N=671,268.

are identified using the occupations assigned in the ODNB biographies, as in the results presented thus far, or based on the occupations self-reported in the patent data. Table 11 presents the top ten verbs associated with engineers based on the matched patent-ODNB data set. In these results, engineers are identified using the occupations reported in the patent data (based on each inventor’s modal occupation) and the comparison group is made up of those individuals in the matched data set with a unique modal occupation other than engineering. Note that this data set includes a much smaller set of biographies, so the results are not as strong as those shown above. Despite that, a number of the terms shown in Table 11, most notably

Born before 1800		Born 1800 or later	
Verb stem	t-stat	Verb stem	t-stat
build	22.46132	design	17.86426
design	15.05358	build	17.33088
employ	10.21637	construct	9.799877
construct	8.489501	consult	6.720318
erect	8.451259	complete	5.592975
make	7.227762	lay	5.573815
patent	6.259257	patent	5.036249
improve	5.873333	report	4.895048
complete	4.945794	act	4.480251
supply	4.936719	propose	3.731473

Table 10: Verbs that define engineers born before vs. after 1800

“design,” are also found in the tables above.

Verb stem	p-value	Sharpened p-value	Verb stem	p-value	Sharpened p-value
design	0.0001	0.014	cast	0.0065	0.242
erect	0.0003	0.025	develop	0.0083	0.242
drive	0.0004	0.025	manufacture	0.0083	0.242
construct	0.0043	0.242	install	0.0136	0.315
achieve	0.0057	0.242	apprentice	0.0139	0.315

Table 11: Verb stems associated with engineers based on matched patent-ODNB data

Estimated coefficients and t-statistics based on robust standard errors. Sharpened p-values are calculated using the approach from Anderson (2008). Regressions include verb and individual fixed effects. N=41,940 (180 biographies with unique modal occupations x 233 verbs).

D British patent data appendix

D.1 Number of patents over time

Figure 6 describes how the number of patents increased across the study period. The graph uses a log scale and excludes patents received as a communication from a person abroad.

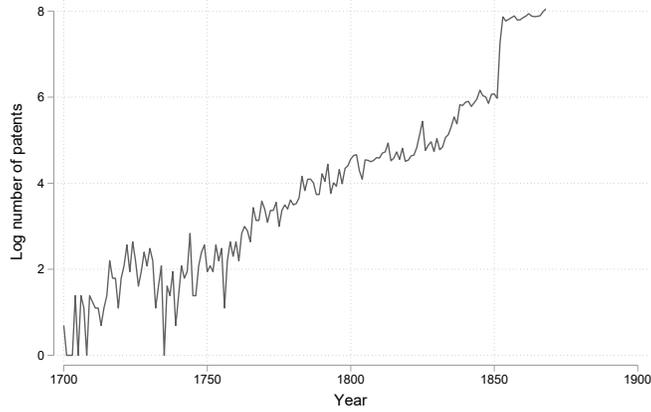


Figure 6: Number of patents by year, 1700-1868 (log scale)

D.2 Patent linking appendix

This section discusses the procedures used to link up patent entries associated with the same unique inventor. At the outset, it is important to recognize that this linking problem is different in a number of important ways than the more well-known problem of linking individuals across various censuses (see Abramitzky *et al.* (2021) and Bailey *et al.* (2020) for discussions of census linking). The most important differences are:

1. Unlike standard census to census linking, the linking undertaken in this paper aims to match up all patents associated with a single individual. This means that rather than searching for unique one-to-one matches, some patents may correctly link to numerous other patents, while many others may correctly not link to any others. One consequence of this is that standard statistics such as link rate are less meaningful in my context.
2. A second important difference relative to the standard census matching problem is that, because patenting is a rare activity typically undertaken by a relatively elite group, I am working with a much smaller universe of observations that need to be linked. Working with a much smaller sample makes linking easier, since it means that it is much less likely that an observation for one individual will have observations for multiple other individuals that are plausible matches. Working with a small universe (not sample) of observations also means that a manual linking approach, similar to the one pioneered by Ferrie (1996), can be used.
3. A third important difference has to do with the quality of the underlying data in my sample. Unlike an historical census, which is collected by thousands of enumerators talking with individuals who themselves may not be literate, and may not even speak the same language well, the patent data that I study was provided and collected by a relatively elite group of individuals. Literacy was almost certainly universal within this group. Moreover, patent filers had strong incentives to ensure that their information was registered correctly, since incorrect filings could potentially raise subsequent legal issues. These differences mean that the underlying data is likely to have substantially fewer errors than

raw census microdata. As one indicator of this, I do not find any nicknames, such as “Bill” or “Bob”, in the data. This does not eliminate all name errors, since there are transcription errors, but it means that one important source of error in standard census linking is unlikely to be substantial in my setting.

4. A fourth difference relative to standard linking problems is that I am working with a different, and in many ways richer, set of information to link on. The examples provided below illustrate the type of data that goes into my links. One implication of this rich set of linking data is that we can typically have a high level of confidence in individual links. A second consequence is that implementing automated linking methods in this setting is likely to be more challenging, another reason to prefer a manual linking procedure.

Given these features, I have chosen to use a manual linking procedure. This procedure involves the following steps:

1. First, I manually reviewed the names and cleaned up obvious transcription errors.
2. Next, I use automated methods to parse names into separate first name and surname fields. This is relatively straightforward except that it requires the removal of suffixes such as “Jr.” or “the younger”.
3. Next, in an Excel file, I sort the data based on (i) first name and (ii) surname and then work down the list of patents to identify potential matches. In the majority of cases, similar names will be located near one another, unless there has been a transcription error in one of the first few letters of the first name. For each potential match, I review available information including the full name, occupation, location, patent description, and co-inventors (see examples below) in order to identify matches.
4. After fully working through the data once, I then re-sort the data based on (i) surname and then (ii) first name and repeat the procedure. Under this sorting approach, entries for the same individual should be very close to one another

unless there has been a serious transcription error in the first few letters of the surname or in the procedure used to parse out surnames.

The best way to get a sense of the information that goes into forming a match is to review some examples. A somewhat arbitrary place to start is to look at the first few entries in the dataset when sorting by first name. These are presented in Table 12. One thing that can be seen in this table is that, because the universe of entries is small, there are quite a few obviously unique names. There are also a number of obvious potential matches, such as those associated with Abraham Buzaglo and Abraham Henry Chambers. A transcription error can be seen in the data, in the last line, but when sorting by either first name or surname that entry will still end up near the other patents by the same individual. It is not hard to imagine working down this list and identifying likely matches. Of course, there are other names that are much more common, so it is not always this easy.

Before coming to some more challenging examples, it is useful to get a sense of the information that goes into making a match. Table 13 presents the first few sets of matched patents in the data (sorting by first names) where I have filled in the inventor's location and the patent description from the original sources. We can see that quite a lot of information is available to make matches. Often, one type of information, such as occupation or location, may vary across entries. We can see this in the case of Abraham Buzaglo, though it is worth noting that an experienced reviewer may note that St. Mary-le-Strand and Strand are essentially equivalent and that both are in close proximity to the City of London. The information on type of invention can be quite useful. Even though the first two entries differ in the listed occupation and location, a comparison of the inventions would strongly suggest a match, even if the name wasn't as unique as Abraham Buzaglo. The last two entries, where one had a transcription error in the name, illustrate that exact name matches are not required to identify a link. These entries also highlight how useful coauthor information can be in confirming a link, though even without that, the almost identical patent descriptions would be enough to identify a link.

The entries in Table 13 are representative of the vast majority of matches, which are straightforward. However, it is also useful to consider some more challenging

Patent No.	Pat. Year	Name (as originally entered)	Occupation
7292	1837	Aaron Fearn	Dyer
2166	1797	Aaron Garlick	Manufacturer
393	1713	Aaron Hill	Esquire
5137	1825	Aaron Jennens	Manufacturer and japanners
4558	1821	Aaron Manby	Iron master
9141	1841	Aaron Ryles	Agent
7923	1839	Abel Morrall	
10553	1845	Abel Siccama	Bachelor of arts
2569	1802	Abner Cowell Lea	Manufacturer
6196	1831	Abraham Adolf Moser	Engineer
8744	1840	Abraham Alexander Lindo	Gentleman
2242	1798	Abraham Bosquet	Esquire
7843	1838	Abraham Bury	Esquire
826	1765	Abraham Buzaglo	Gentleman
928	1769	Abraham Buzaglo	Warming machine maker
1211	1779	Abraham Buzaglo	Warming machine maker
7882	1838	Abraham Collen	Esquire
380	1707	Abraham Darby	Smith
5369	1826	Abraham Dixon	Manufacturer
845	1766	Abraham Foster	Peruke maker
5962	1830	Abraham Garnett	Esq.
4441	1820	Abraham Henry Chambers	Esquire
4527	1821	Abraham Henry Chambers	Esquire
4906	1824	Abraham Henry Chambers	Esquire
5114	1825	Abraham Henry Chambers	Esquire

Table 12: First 25 entries in the patent data when sorting by first name

examples, which highlight the advantages of a manual linking procedure. Entries for patentees named Henry Smith, a fairly common name, are shown in Table 14. The first two columns include the patent number and patent title for each patent with an inventor with this name. The third column presents the unique individual ID generated by my name matching process. The first two Henry Smiths (nos. 3804 and 3805) are unique. The third Henry Smith (no. 3806) is matched to three different patents. For this inventor, the match between patents 9291 and 10808 is fairly straightforward, but the match to patent 12266 is more difficult. In that case, the inventor has moved to a different town and the entry is missing an occupation. However, the very specific nature of the invention, railway wheels, makes it extremely unlikely that these are coming from a different inventor. Thus, patent no. 12266 is matched to the

Pat. No.	Pat. Year	Name (pre-cleaning)	Occupation	Location	Invention	Coinventors
826	1765	Abraham Buzaglo	Gentleman	City of London	Machine for warming rooms of all sizes with a coal fire	
928	1769	Abraham Buzaglo	Warming machine maker	Catherine St., Mary-le-Strand	New invented warming machine	
1211	1779	Abraham Buzaglo	Warming machine maker	Strand, Westminster, Middlesex	New invented muscular strength and health restoring exercise	
4441	1820	Abraham Henry Chambers	Esquire	Bond St., Middlesex	Improvement in the preparing or manufacturing of substances for the formation of highways and other roads	
4527	1821	Abraham Henry Chambers	Esquire	Bond St., Middlesex	Improvements in the manufacture of building cement, composition, stucco...	
4906	1824	Abraham Henry Chambers	Esquire	New Bond St., Middlesex	Improvements in preparing and paving horse carriage ways	
5114	1825	Abraham Henry Chambers	Esquire	Stratford Pl., Mary-le-Bone	New filtering apparatus	Ennis Chambers, Charles Jeppard
1843	1791	Abraham Hill	Saw maker	Whiteley Wood, Sheffield	New method of making scythes with steel blades	
1972	1793	Abraham Hill	Saw maker	Whiteley Wood, Sheffield	New invented method of making with iron backs steel knives for cutting hay and straw	
11737	1847	Abraham Solomons	Merchant	City of London	Certain improvements in the manufacture of charcoal and other fuel	Bondy Azulay
12165	1848	Abraham Solomons	Merchant	City of London	Improvements in the manufacture of gas, tar, charcoal and certain acids	Bondy Azulay
10547	1845	Adam Og Den	Gentleman	Hey Chapel, Ashton-under-Lyne	Certain improvements in machinery for preparing and cleaning wool, cotton and similar fibrous substances	John Sykes
11798	1847	Adam Ogden	Wool cleaner and machine maker	80 Huddersfield, York	Improvements in machinery for cleaning wool, cotton, and similar fibrous substances	John Sykes

Table 13: First few matches in the data when sorting by first name

Henry Smith with individual ID 3806. The fourth entry, individual ID 3807, could potentially be a match for the patent with individual ID 3805 because the name and location are the same and the timing is proximate. However, Birmingham is a large city and there is no similarity in the subject matter of the invention. Therefore, these two entries are not matched. Finally, the Henry Smith with individual ID 3808 is matched to two patents. Both are straightforward given the occupation and location. These are more representative of the types of matches that are common in the database.

Pat No.	Pat year	Indiv. ID	Name	Occupation	Address	Patent title
2658	1802	3804	Henry Smith	Lieutenant, H.M. Navy		New improved vessel or barrel for the more safe and expeditious carriage and conveyance of gunpowder
8446	1840	3805	Henry Smith	Lamp manufacturer	Birmingham	Improvements in gas burners and in lamps
9291	1842	3806	Henry Smith	Engineer	Liverpool	Improvements in the construction of wheels and breaks for carriages
9838	1843	3807	Henry Smith		Birmingham	Improvements in apparatus for fastening doors and in apparatus for giving action to alarms
10241	1844	3808	Henry Smith	Agricultural implement maker	Stamford, Lincolnshire	Certain improvements in the construction and arrangement of hand rakes and horse rakes, and in machinery for cutting vegetable substances
10808	1845	3806	Henry Smith	Engineer	Liverpool	Improvements in the manufacture of wheels for railways, and in springs for railway and other carriages, and in axle guards for railway carriages
11638	1847	3808	Henry Smith	Agricultural implement maker	Stamford, Lincolnshire	Certain improvements in machinery for cutting and separating vegetable substances
12266	1848	3806	Henry Smith		Vulcan Works, West Bromwich	Improvements in the manufacture of railway wheels

Table 14: Names matching for “Henry Smith”

A second example, for the subset of patentees named John Browne, is shown in Table 15. Here, the first two entries are an obvious match. The next two individuals are also a clear match given the address and occupation. The fifth John Browne, from Brighton, also appears to be unique. The remaining five patents are all matched to one individual, no. 5485. There is some question about whether these should be matched given that there is an address change and there does not appear to be a commonality in the subject matter of the inventions. However, patent 12452 makes it clear that the patent listing an address on New Bond Street belongs to the same individual who later lived on Great Portland St. The difficult patent is then 12326, which has a different address but the same occupation as patent no. 12452. However,

it is clear that the individual moved during this period and a search of Google maps reveals that Osnaburgh St. is in very close proximity to both New Bond St. and Great Portland St. in London. Together, this information is enough to conclude that all five patents likely came from the same individual.

Pat No.	Pat year	Indiv. ID	Name	Occupation	Address	Patent title
5496	1827	5480	John Browne	Merchant and copartner	Bridgewater, Somerset	A certain composition or substance which may be manufactured or moulded either into bricks or into blocks of any form...
6742	1834	5480	John Browne	Merchant	Bridgewater, Somerset	An improved instrument or apparatus for ascertaining levels
7863	1838	5482	John Browne	Esquire	Castle St., Middlesex	Improvements in paving roads and streets
8050	1839	5482	John Browne	Esquire	Castle St., Middlesex	Improvements in saddles and stirrups for horses and other animals
9349	1842	5484	John Browne	Gentleman	Brighton	Improvements in the manufacture of mud boots and overalls
10104	1844	5485	John Browne	Esquire	New Bond St., Middlesex	Improvements in urinary utensils
10180	1844	5485	John Browne	Esquire	New Bond St., Middlesex	Improvements in apparatus for protecting the human face, or part of the human face, from the inclemency of the weather
12326	1848	5485	John Browne	Gentleman	Osnaburgh St., Middlesex	Improvements in fire escapes, and in apparatus to facilitate persons employed in cleaning windows
12452	1849	5485	John Browne	Gentleman	Formerly of Bond St., now of Great Portland St.	Improvements in constructing and rigging vessels, and improvements in atmospheric and other railways
12686	1849	5485	John Browne	Esquire	Great Portland St., Middlesex	Improvements in apparatus to assist combustion in stoves or grates

Table 15: Names matching for “John Browne”

To summarize, it is hoped that these examples provide a useful illustration of the linking procedure used in this paper. It should be clear that the combination of a relatively small universe of observations, together with a rich set of data to match on, lend themselves to a manual matching procedure, and that such a procedure can generate matches where, in the substantial majority of cases, there is little doubt about the accuracy of the resulting link.

D.3 List of top patent holders

Table 16 lists those patent holders with 10 or more patents during the 1700-1849 period, excluding communicated patents. This list includes a number of famous engineers. Many of the names on this list appear in the ODNB (indicated in italics).

Inventor	Pats.	Inventor	Pats.
William Church	18	<i>Robert William Sievier</i>	11
<i>Samuel Hall</i>	17	William Chapman	11
<i>Joseph Bramah</i>	16	Christopher Nickels	11
<i>Marc Isambard Brunel</i>	15	<i>David Napier</i>	11
Joseph Clisild Daniell	15	Augustus Applegarth	11
William Palmer	14	<i>Thomas Hancock</i>	11
Robert Dickinson	14	John George Bodmer	11
Elijah Galloway	13	Joseph Manton	10
<i>Edward Massey</i>	13	Thomas Robinson Williams	10
John Heathcoat	13	<i>William Hale</i>	10
<i>John Dickinson</i>	13	<i>Joseph Maudslay</i>	10
<i>William Congreve</i>	13	Richard Witty	10
William Crofts	12	<i>Samuel Brown</i>	10
Lemuel Wellman Wright	12	<i>Edmund Cartwright</i>	10
Andrew Smith	12	William Losh	10
Benjamin Cook	12	Anthony George Eckhardt	10

Table 16: Top patent filers during the 1700-1849 period

Top patent filers from 1700-1849, excluding communicated patents. Names in italics have been matched to the ODNB.

D.4 Details on occupation groups in the patent data

Table 17 presents the most common occupations within each of the broad occupation groupings used in my analysis. We can see that some groups, such as engineers, esquires, merchants and gentlemen, have a few very common occupations. Others, particularly those in manufacturing, often have a much larger number of unique occupations, each with fewer patents.

Agric/Food/Drinks		Machinery & Tools		Gentleman	
Farmer	71	Machinist	159	Gentleman	2037
Brewer	44	Machine maker	151	Baronet	21
Miller	30	Mechanic	128	Knight	17
Sugar refiner	21	Watch maker	112		
Distiller	19	Gun maker	66	Other	
		Mathematical inst. maker	44	Artist	65
Chemical		Engine maker	29	Printer	56
Chemist	232	Smith	22	Manager	30
Manufacturing chemist	88	Cutler	20	Stationer	30
Apothecary	18			Hatter	23
Practical chemist	12	Merchant		Agent	21
Soap boiler	12	Merchant	679	Master mariner	21
		Wine merchant	17		
Construction		Timber merchant	11	Prof. services	
Millwright	59	Grocer	10	Surgeon	114
Builder	49			Clerk	75
Carpenter	38	Metal & Mining		Doctor of medicine	49
Plumber	35	Ironmonger	106	Architect	48
Potter	23	Iron master	100	Patent agent	44
		Brass founder	96	Optician	36
Engineering		Iron founder	90	Mechanical draughts	36
Engineer	1250	Whitesmith	27	Surveyor	33
Civil engineer	540	Iron manufacturer	23		
Gas engineer	13			Textiles	
Millwright & engineer	9	Misc. Manufacturing		Cotton spinner	113
		Manufacturer	328	Lace manufacturer	98
Esquire		Coachmaker	64	Clothier	68
Esquire	840	Musical instrument maker	62	Dyer	64
		Cabinet maker	44	Calico printer	53
		Paper maker	36	Weaver	43
		Tanner	33		
		Hat manufacturer	27		

Table 17: Major occupations within each broad grouping

Counts are based on data from 1700-1849.

Table 18 provides counts of the occupation groupings used in the analysis for 1700-1849. Given my focus on engineers, a couple of additional points about that

occupation grouping are warranted. First, some inventors listing “engineer” as an occupation also list another occupation. This is not very common, but typically when it occurs the other occupation is some type of manufacturing. Individuals who list engineer together with a second occupation are counted as engineers in my analysis. Second, civil and other types of engineers (e.g. “consulting engineers”) are also counted as engineers for the purposes of my analysis. Third, I exclude from the engineers category those described as “engine makers” as well as mining engineers (which includes “coal viewers”). There is some question about whether these should be treated as engineers or instead classified with, respectively, the machinery manufacturers and miners so, in the Appendix, I also consider robustness results including these groups as engineers. Ultimately, this makes little difference because neither engine makers nor mining engineers are common. Military engineers are also excluded from the engineers category. They are treated the same as other military officers.

Industry	Patents	Industry	Patents
Ag/Food/Drinks	269	Merchants	635
Chemical Manuf.	474	Mining & Metals	759
Construction	410	Misc. Manuf.	1562
Engineers	1726	Textile Manuf.	957
Esquire	754	Prof. services	635
Gentry	1745	Other	833
Machinery & Tools	1068	Unknown	795

Table 18: Broad occupation categories used in the main analysis, 1700-1849

Data cover 1700-1849. Excludes communicated patents.

D.5 List of top patenting engineers by decade

Table 19 lists the top 5 individuals filing patents with an engineering occupation (in the patent data) in each decade up to the 1840s (counting only patents where they list their occupation as engineer). This provides a rough guide to prominent engineers, though note that engineers may fail to make the list because their patents were spread across different decades, and some of these individuals may have filed additional patents in a decade under a different occupation.

Decade	Name	Pats.	Decade	Name	Pats.
1720s	Thomas Benson	1	1800s	Joseph Bramah	6
	Isaac De La Chaumette	1		Archibald Thompson	4
1730s	John Kay	1		Samuel Miller	4
	Thomas Benson	1		William Chapman	4
1740s	Moses Hadley	1		Richard Trevithick	4
	John Wise	1	1810s	Samuel John Pauly	5
1750s	George John	1		William Davis	5
	1760s	Robert Mackell		1	Marc Isambard Brunel
William Blakey		1		Bryan Donkin	3
Jonathan Greenall		1	Joseph Bramah	3	
Thomas Perrins		1	1820s	Lemuel Wellman Wright	9
Charles Nicholas Michel Babu	1	Jacob Perkins		7	
1770s	John Budge	1		James Fraser	6
	John Rastrick*	1		John Hague	6
	Christopher Chrisel	1		James Neville	5
	Matthew Wasbrough	1	1830s	John Ericsson	11
1780s	James Watt	5		Joseph Gibbs	10
	Robert Cameron	4		Andrew Smith	9
	William Playfair	3		John George Bodmer	7
	John Besant	1	Joseph Whitworth	7	
	Joseph Hateley	1	1840s	Henry Bessemer	13
1790s	James Rumsey	3		Joseph Maudslay	8
	Joseph Bramah	3		John George Bodmer	8
	Joseph Hateley	2		Elijah Galloway	8
	Thomas Mead	2		John Coope Haddan	7
	William Whitmore	2			

Table 19: Top engineer inventors by decade

Patents indicate the number of patents that the inventor produced in a decade where their occupation was listed as an engineer. Inventors in italics appear in the ODNB. *John Rastrick is not included in the ODNB, but his son of the same name was included.

D.6 Additional details on the BPO technology category data

Table 20 describes the number of patents and share of patents for the most common technology categories by period. Before 1750, the largest category of inventions was Water and Fluids, which includes pumps, water-wheels, etc. Weaving and Spinning were important in the early period and grew even more important over time. Three other technologies associated with the Industrial Revolution, namely Steam Engines, Metals and Metallic Substances, and Railways, also became much more important over time, while technologies such as Musical Instruments and Coaches a Road Conveyances declined.

1700-1749			
1700-1749	Technology category	Patents	Share
1	Water and Fluids	94	0.051
2	Navigation I: Ship-Building, Rigging, and Working	79	0.043
3	Weaving and Preparing for Weaving	71	0.038
4	Spinning and Preparing for Spinning	68	0.037
5	Weapons of Defence, Ammunition	68	0.037
6	Coaches and Other Road Conveyances	64	0.035
7	Motive-Power and Propulsion	57	0.031
8	Musical Instruments	46	0.025
9	Medical and Surgical Treatments	46	0.025
10	Steam-Engines and Boilers	45	0.024
1750-1799			
	Technology category	Patents	Share
1	Water and Fluids	132	0.050
2	Weaving and Preparing for Weaving	119	0.045
3	Spinning and Preparing for Spinning	110	0.042
4	Metals and Metallic Substances	106	0.040
5	Medical and Surgical Treatments	99	0.038
6	Coaches and Other Road Conveyances	91	0.035
7	Navigation I: Ship-Building, Rigging, and Working	84	0.032
8	Fireplaces, Stoves, Furnaces, Ovens, and Kilns	67	0.025
9	Motive-Power and Propulsion	64	0.024
10	Steam-Engines and Boilers	62	0.024
1800-1849			
	Technology category	Patents	Share
1	Steam-Engines and Boilers	751	0.054
2	Motive-Power and Propulsion	722	0.052
3	Spinning and Preparing for Spinning	711	0.051
4	Weaving and Preparing for Weaving	694	0.050
5	Railways and Railway Rolling-Stock	492	0.035
6	Metals and Metallic Substances	472	0.034
7	Navigation I: Ship-Building, Rigging, And Working	402	0.029
8	Smoke Prevention: Consumption of Fuel	354	0.025
9	Coaches and Other Road Conveyances	353	0.025
10	Printing	305	0.022

Table 20: Top ten technology categories by period (excluding comm. pats.)

E British patent analysis appendix

E.1 Additional comparisons to specific occupation groups

This appendix provides additional comparisons between engineers and a selection of more detailed occupation groups that have been highlighted as making an important contribution to innovation during the Industrial Revolution. In particular, I compare engineers to watchmakers (including clockmakers), millwrights and wheelwrights, engine makers, instrument makers, and a general category encompassing

those described as machine makers, machinists or mechanics. I also considered comparing to coal viewers/mining engineers, but there are too few patents by inventors listing those occupations to allow for any useful comparison.

The top panel of Figure 7 describes patents by each of these groups across the study period. Note that, as in the main analysis, the engineers category includes civil engineers. If an individual lists their occupation as spanning both engineering and another one of these groups, such as “Engineer and millwright”, I count the patent in both groups to allow for a fair comparison. It is clear from the top panel of this figure that only among engineers do we see a take-off in patenting in the decades just after the onset of the Industrial Revolution. In fact, the difference is so extreme that, when graphed in levels, it is hard to see much action among the other occupation groups, with the exception of the broader “Machine maker, machinist and mechanic” category, which shows some increase after 1820. To deal with this, the bottom panel provides the same figure but using a log scale on the y-axis. There we can see some more interesting patterns. Patents by watchmakers, for example, increased substantially between 1730 and 1760, before leveling off. This shows that watchmakers were making an important contribution to innovation in the middle of the eighteenth century, a pattern that is in line with other evidence on the importance of watchmakers at this time (Kelly & Ó Gráda, 2016).

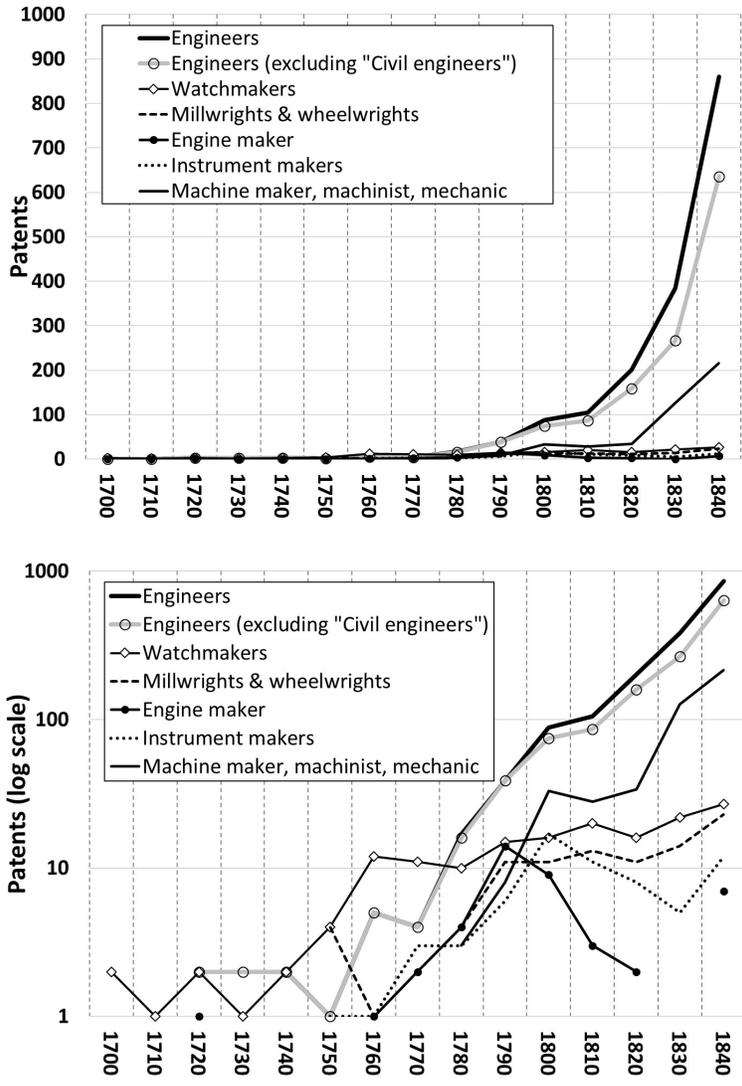


Figure 7: Comparing engineers to a selection of detailed occupations

Excludes communicated patents.

E.2 Patents per inventor using alternative ways of identifying engineers in the patent data

In the analysis in Section 4.1.1, I identify engineers as those where engineering is the modal occupation among the occupations listed in each inventor's patents, and those

without a unique modal occupation are excluded from the analysis. In Table 21, I look at results for the number of patents per inventor when using other alternative definitions of engineer, but always using the occupations from the patent data. To ease comparison, Column 1 presents results following the approach used in the main text. Note that this differs from the estimates shown in Table 3 only because I am not estimating a separate coefficient for manufacturers. In Column 2, I present results where I still identify engineers based on having engineering as a unique modal occupation, but instead of dropping those without a unique modal occupation I include them as non-engineers. In Column 3, I count as engineers anyone with at least one patent listing engineering as their occupation. In Column 4, engineers are those with at least one-third of their patents listing engineering as their occupation. In Column 5, engineers are those with two-thirds of their patents listing engineering as their occupation. This is a fairly restrictive definition which excludes a number of people who clearly should be counted as engineers, including William Chapman (inventor of the railroad bogie), William Symington (builder of the first practical steamboat), and William Playfair.

	DV: Number of patents per inventor				
	(1)	(2)	(3)	(4)	(5)
	Approach from main text	Including those without unique modal occupations	Engineer is anyone with a patent listing engineering	Engineers have \geq one-third patents listing engineering	Engineers have \geq two-thirds patents listing engineering
Engineer	0.606*** (0.0906)	0.546*** (0.0901)	0.884*** (0.0938)	0.722*** (0.0867)	0.488*** (0.0888)
Tech. cat. FEs	Yes	Yes	Yes	Yes	Yes
Observations	7,966	8,327	8,327	8,327	8,327
R-squared	0.044	0.041	0.060	0.050	0.039

Table 21: Patents per inventor using alternative definitions of engineer

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS regressions with robust standard errors in parenthesis. The unit of observation is an inventor. The outcome variable is the number of patents per inventor across all years. The explanatory variable is an indicator for whether the inventor's modal occupation is engineer. All columns include controls for the modal technology category for each inventor within each period. In all of these, if there is a tie for the modal category then one is selected randomly.

All of these alternative results provide strong evidence that engineers were more productive than other types of inventors. It is interesting to note that the size of the coefficient on engineers actually increases as I apply less restrictive criteria for identifying engineers. This signals that in identifying engineers, type one errors (failing to correctly identify engineers) are probably dominating type two errors (incorrectly identifying those who are not engineers as engineers), so that when more restrictive criteria are used, more productive individuals, who look like they should be classified as engineers, are instead being grouped in the non-engineer category. In any case, Column 1 shows that the use of modal industry while excluding those inventors without a unique modal industry, as is done in the main text, represents a reasonable middle-ground approach.

E.3 Patents per inventor using biographical data to identify engineers

Next, I consider results where I identify engineers using information from the ODNB rather than the self-reported occupations from the patent data. As described in Section 2, there are two ways that I can use the ODNB data to identify engineers. The first is simply to use the occupational classifications provided by modern historians. This is done in Column 1 of Table 22. The second approach predicts whether someone is likely to be an engineer based on the verb stems appearing in the full text of their ODNB biography. This is done in Columns 2-4 of Table 22 using two different cutoffs of the predicted engineer score to identify engineers, in Columns 2 and 3, as well as the continuous score in Column 4. Both of these approaches have the advantage that they are not based on self-reported occupations, and the second approach is particularly valuable because it is robust to changes in the popularity of engineer as an occupation title over time. Columns 5-8 repeat the same set of results while including a full set of fixed effects for the modal technology category that each individual worked in.

Across all of these results, there is clear evidence that engineers generated more patents than other types of inventors. This tells us that the finding in the main text—that engineers produced more patents than other types of inventors—is not driven simply by more productive inventors self-reporting their occupation as engineer.

DV: Patents per inventor				
Engineers identified by:	ODNB occ. (historians)	Predicted based on verb stems in bio		
		1 s.d. cutoff	1.5 s.d. cutoff	Continuous
<i>A: Baseline specification</i>				
	(1)	(2)	(3)	(4)
Engineer	0.739*** (0.251)	0.985** (0.433)	1.084 (0.697)	0.728* (0.375)
Constant	2.018*** (0.119)	2.145*** (0.109)	2.189*** (0.107)	1.994*** (0.144)
Observations	633	633	633	633
R-squared	0.016	0.012	0.007	0.014
<i>B: With individual modal technology category FEs</i>				
	(5)	(6)	(7)	(8)
Engineer	0.527* (0.313)	0.882* (0.474)	1.337* (0.693)	0.763** (0.342)
Constant	1.250*** (0.240)	1.029*** (0.122)	0.916*** (0.190)	0.969*** (0.162)
Observations	633	633	633	633
R-squared	0.199	0.201	0.202	0.205

Table 22: Patents per inventor using the ODNB to identify engineers

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Robust standard errors in parentheses. This analysis is based on every individual in the ODNB listed as working in science, technology, manufacturing or engineering. In Column 1, engineers are identified based on whether they were classified as an engineer by the historians who produced the ODNB. In Columns 2-4, engineers are identified using the predicted probability that an individual was an engineer based on the procedure described in Section 2, with individuals with scores of 1 or 1.5 s.d. above the average classified as engineers in Columns 2 and 3, respectively, and the continuous measure used in Column 4. Columns 5-8 repeat the same set of regressions but including a fixed effects for each individuals' modal technology category.

E.4 Results including other groups as engineers

In the results presented in the main text, the engineers category excludes those described as engine builders as well as mining engineers (also called coal viewers). In Table 23, I present results including these groups as engineers rather than in the machinery manufacturers or mining categories.⁶² These results are effectively identical to those presented in the main text, which tells us that the decision of whether or not to include engine builders and mining engineers in the engineering category has no impact on my results.

	DV: Number of patents per inventor					
	All years (1)	All years (2)	1770- 1789 (3)	1790- 1809 (4)	1810- 1829 (5)	1830- 1849 (6)
Engineer	0.677*** (0.0844)	0.629*** (0.0876)	0.805** (0.380)	0.740*** (0.220)	0.315** (0.125)	0.474*** (0.0911)
Manufacturer	0.0596* (0.0326)	0.0113 (0.0372)	-0.0720 (0.0627)	-0.0184 (0.0602)	-0.0470 (0.0590)	0.00514 (0.0535)
Tech. cat. FEs		Yes	Yes	Yes	Yes	Yes
Observations	7,965	7,965	652	1,209	1,803	4,215
R-squared	0.018	0.047	0.183	0.124	0.064	0.055

Table 23: Patents per inventor including engine makers and mining engineers

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS regressions with robust standard errors in parenthesis. The unit of observation is an inventor. The outcome variable is the number of patents per inventor across all years (Column 1-2) or with 20-year periods (Columns 3-6). The explanatory variable is an indicator for whether the inventor's modal occupation is engineer. Inventors without a unique modal occupation are not included. The regression in Column 2 controls for the modal technology category for each inventor looking across all of that inventor's patents by including a full set of technology category fixed effects. In Columns 3-6, I control for the modal technology category for each inventor within each period. In all of these, if there is a tie for the modal category then one is selected randomly.

⁶²Note that this changes the sample size slightly because it means that some inventors that previously did not have a modal occupation, and were therefore not included in the analysis, now have a modal occupation.

E.5 Additional results using patent renewal data

Table 24 presents a more complete set of regression results using patent renewal data. The results in Panel A are based on OLS regressions, while Panel B presents corresponding results from Probit regressions. All of these results indicate that patents by engineers were more likely to be renewed at both three and seven years, and the results are both large in magnitude and strongly statistically significant. The magnitude of the results generated using OLS and Probit regressions are very similar. Manufacturer-inventors were also more likely to renew their patents, but much less likely than engineers.

Dep. var:	Patent renewed at three years			Patent renewed at seven years		
A. OLS regressions						
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.0555*** (0.00619)	0.0557*** (0.00619)	0.0462*** (0.00899)	0.0244*** (0.00429)	0.0244*** (0.00429)	0.0200*** (0.00637)
Manufacturer	0.0222*** (0.00515)	0.0221*** (0.00517)	0.0140* (0.00772)	0.0124*** (0.00342)	0.0121*** (0.00342)	0.00870* (0.00520)
Year FEs		Yes	Yes		Yes	Yes
Tech. cat. FEs			Yes			Yes
Observations	30,579	30,579	54,736	27,436	27,436	41,214
R-squared	0.003	0.003	0.020	0.001	0.002	0.015
B. Probit regressions (marginal effects)						
	(7)	(8)	(9)	(10)	(11)	(12)
Engineer	0.057*** (0.0064)	0.057*** (0.0064)	0.047*** (0.009)	0.025*** (0.0046)	0.025*** (0.0046)	0.019*** (0.0062)
Manufacturer	0.023*** (0.0054)	0.023*** (0.0054)	0.015* (0.0080)	0.013*** (0.0036)	0.013*** (0.0036)	0.009* (0.0053)
Year FEs		Yes	Yes		Yes	Yes
Tech. cat. FEs			Yes			Yes
Observations	30,579	30,579	54,736	27,436	27,436	41,214

Table 24: Additional results using patent renewal data

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in Columns 1-2, 4-5, 7-8 and 10-11. In Columns 3, 6, 9 and 12, standard errors are clustered by patent number to deal with the fact that patents may appear multiple times if they are classified into multiple technology categories. The analysis in Column 1-3 and 7-9 cover patents originally filed from 1856-1869. The analysis in Columns 4-6 and 10-12 cover patents originally filed from 1853-1866.

E.6 Additional patent quality index results

Tables 25-26 present additional results using the patent quality indices. Table 25 presents more complete results using the same approach taken in the main text. In that approach, engineer and manufacturer patents are identified based on the occupations listed in the entry for each patent. Table 26 presents results from an alternative approach in which engineer and manufacturer patents are identified based on the modal industry of each inventor.

Dep. var:	WRI Index			BCI index		
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.0825*** (0.0270)	0.0689*** (0.0258)	0.0389 (0.0306)	0.250*** (0.0359)	0.251*** (0.0381)	0.230*** (0.0435)
Manufacturer	-0.0596*** (0.0192)	-0.0653*** (0.0187)	-0.0510** (0.0252)	-0.0598*** (0.0171)	-0.0676*** (0.0181)	-0.105*** (0.0306)
Year FEs		Yes	Yes		Yes	Yes
Tech. cat. FEs			Yes			Yes
Observations	12,622	12,616	18,473	12,622	12,616	18,473
R-squared	0.002	0.105	0.134	0.010	0.036	0.058

Table 25: Additional results using patent quality indices

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS regressions. Columns 1-2 and 4-5 present robust standard errors. In Columns 3 and 6, standard errors are clustered by patent number to deal with the fact that patents may appear multiple times if they are classified into multiple technology categories. The analysis in Column 1-3 covers patents originally filed from 1856-1869. The analysis in Columns 4-6 covers patents originally filed from 1853-1866.

In the patent quality index results presented in the main text as well as the other tables in the appendix, engineers are identified based on the occupations self-reported in the patent data. In Table 27 I take an alternative approach in which engineers are identified either based on the judgement of modern historians (Column 1) or using the predicted probability that they were an engineer based on the verb stems included in their ODNB biography using the procedure outlined in Section 2. The sample of inventors included in this analysis includes any individual appearing in the ODNB classified as working in science, technology, engineering or manufacturing and who can also be matched to one or more patents. For both of these sets of results, I focus

Dep. var:	WRI Index			BCI index		
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.127*** (0.0300)	0.110*** (0.0297)	0.0822** (0.0335)	0.273*** (0.0386)	0.273*** (0.0409)	0.278*** (0.0475)
Manufacturer	-0.0488*** (0.0189)	-0.0606*** (0.0184)	-0.0470* (0.0242)	-0.0860*** (0.0161)	-0.0941*** (0.0170)	-0.130*** (0.0278)
Year FEs		Yes	Yes		Yes	Yes
Tech. cat. FEs			Yes			Yes
Observations	12,622	12,616	18,473	12,622	12,616	18,473
R-squared	0.003	0.106	0.135	0.013	0.039	0.062

Table 26: Patent quality index results using inventors' modal industry

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS regressions. Columns 1-2 and 4-5 present robust standard errors. In Columns 3 and 6, standard errors are clustered by patent number to deal with the fact that patents may appear multiple times if they are classified into multiple technology categories. The analysis in Column 1-3 covers patents originally filed from 1856-1869. The analysis in Columns 4-6 covers patents originally filed from 1853-1866.

on the preferred BCI patent quality index. When using the predicted score to identify engineers, I consider two alternative cutoffs, 1 s.d. above the mean (Column 2) or 1.5 s.d. above the mean (Column 3) as well as using the continuous measure (Column 4). All of these results show strong evidence that engineers produced higher quality patents than other inventors appearing in the ODNB.

DV: BCI patent quality index				
Engineers identified by:	ODNB occ. (historians)	Predicted based on verb stems in bio		
		1 s.d. cutoff	1.5 s.d. cutoff	Continuous
	(1)	(2)	(3)	(4)
Engineer	0.145*** (0.0370)	0.296*** (0.0662)	0.484*** (0.111)	0.314*** (0.0745)
Constant	0.178*** (0.0211)	0.192*** (0.0174)	0.197*** (0.0166)	0.106*** (0.0294)
Observations	1,387	1,387	1,387	1,387
R-squared	0.011	0.023	0.035	0.039

Table 27: Patent quality index results using ODNB engineer identifiers

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Robust standard errors in parentheses. The unit of observation in this analysis is the patent. The sample includes all patents linked to individuals in the ODNB listed as working in science, technology, manufacturing or engineering. In Column 1, engineers are identified based on whether they were classified as an engineer by the historians who produced the ODNB. In Columns 2-4, engineers are identified using the predicted probability that an individual was an engineer based on the procedure described in Section 2, with individuals with scores of 1 or 1.5 s.d. above the average classified as engineers in Columns 2 and 3, respectively, and the continuous measure used in Column 4.

E.7 Additional results and discussion using the Great Exhibition data

The Great Exhibition of 1851 was the first major “World’s Fair.” As discussed in Moser (2005) and Moser (2012), inclusion in the Great Exhibition can be used as an indicator of the quality of an invention, since only the best inventions were chosen by expert juries. The full listing of exhibits in the Great Exhibition of 1851 were digitized by Moser, who generously shared them with me. Moser’s digitized data includes an indicator for whether an exhibit was patented based on information from the description of each invention.

For each patented invention in Moser’s database, I attempt to match the exhibitor (or in some cases a different inventor, if one is named in the exhibit description) to those patent holders in my database from 1830-1849. This match was done manually using the surname and first initial of each inventor, their address, as well as details on the nature of the invention. In total, out of the 683 patented inventions with inventors listing an address in England or Wales in Moser’s data, I am able to match

351 to individuals in my patent data, or just over 50%. There are a number of reasons why I may fail to find match. For example, some exhibits were done by companies rather than individuals, which makes it impossible to match to an individual inventor. Also, for those with common names it is often impossible to make a match given that only first initials are provided in the exhibition data, and in some cases (e.g. “Jones and Sons”) even first initials are not available. In total, 14.4% of the inventors that patented from 1830-1849 were engineers, but they make up 21% of those who matched to exhibits.

Table 28 presents some additional results using the Great Exhibition data. The first two columns present OLS regressions while the second two columns show marginal effects from Probit regressions. In Columns 1 and 3, the sample includes all inventors who filed a patent from 1830-1849 and the outcome variable is whether they match to an exhibition. We can see that both the OLS and Probit results tell a similar story. Engineers were more likely to match to patented exhibits in the Great Exhibition than other types of inventors and, while manufacturer-inventors were also more likely to exhibit, they were less likely to do so than engineers (the difference between the engineer and manufacturer coefficients is statistically significant at the 95% confidence level in both specifications).

The results in Column 2 and 4 look at whether, conditional on exhibiting, an inventor was more likely to win an award. These results indicate that, conditional on being an exhibitor, both engineers and manufacturer-inventors were more likely to win awards than other types of inventors, but the two groups are statistically indistinguishable from each other in their likelihood of winning an award.

E.8 Additional results measuring patent quality using the ODNB

This section provides some additional discussion of results using appearance in the ODNB to assess patent quality (Table 4 Column 6). Note first that this analysis is not based on the main ODNB dataset, which identifies engineers based on the occupations listed in the ODNB. Instead, this analysis is based on a dataset constructed by (i) starting with all patent holders who filed two or more patents, (ii) searching and manually matching these patent holders to the ODNB database, and (iii) looking

	OLS regressions		Probit marginal effects	
	Exhibited (1)	Awarded (2)	Exhibited (3)	Awarded (4)
Engineer	0.0441*** (0.0131)	0.138* (0.0742)	0.0468*** (0.0144)	0.137* (0.0723)
Manufacturer	0.0159* (0.00835)	0.157** (0.0614)	0.017* (0.0090)	0.0157*** (0.0609)
Observations	4,469	329	4,469	329
R-squared	0.003	0.022		

Table 28: Additional results using Great Exhibition data

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parenthesis. In the “Exhibited” columns, the sample is the set of all inventors who patented from 1830-1849 and the outcome variable is an indicator for whether an inventor matches to a patented exhibit. In the “Awarded” column, the sample is the set of patent holders who match to a patented exhibit in the exhibition database and the outcome variable is an indicator for whether the exhibit received an award. In both types of regressions, the explanatory variables are based on the modal occupation of each inventor. Inventors without unique modal occupations are not included in the analysis.

at how the probability that individuals in the patent data were found in the ODNB data varies based on their occupation classification, where the occupation classifications come from the patent data. Constructing the dataset in this way allows a fair comparison between the occupations appearing in the patent data.

There are roughly two thousand individuals with two or more patents in the 1700-1849 period. I manually search for each of these individuals in the ODNB, verifying a match by comparing information in the ODNB to the information available in the patent data. In many cases the ODNB lists the actual patent number of patents filed by famous inventors. This procedure yields 245 matches, a match rate of 11.9% (this rate rises to 18.7% for inventors with three or more patents and 23.8% for those with four or more). Given that this is a careful manual match relying on multiple sources of information for verification, it is unlikely that there are many false matches in the matched set. It is possible that some matches are missing due to, for example, misspellings and other sources of name variation, but these are unlikely to be systematic across different occupation groups.

Of the patent holders matched to the ODNB data, the three most common broad

occupation groups (based on occupations in the patent data) are engineers, manufacturers, and gentlemen/esquires. Table 29 describes the number of inventors in each of these three main groups with two or more patents (first column) which were searched for in the ODNB database, the number actually found in the ODNB databases (second column), and a breakdown of those found in the ODNB database that were born up to 1780 (third column) or after 1780 (fourth column).⁶³ The most important pattern to note here is that engineers made up 15.5% of the inventors searched for in the ODNB database but 26.9% of those found in ODNB, and 34.2% of those born after 1780. This suggests that, even conditional on having produced at least two patents, engineers were more likely to have become noteworthy individuals than other types of patentees. Since inventors were likely to become noteworthy through the success of their inventions, this indicates that engineers were more likely to produce noteworthy inventions than other types of inventors.

A notable feature of the data in Table 29 is that engineers made up over one third of those inventors with at least two patents born after 1780 that achieved a substantial level of prominence in their lives, a greater share than any other group, even when all manufacturing inventors are grouped together. This provides another indication of the substantial contribution made by engineer inventors to technological progress.

In fact, these figures likely understate the relative success of engineers, since other types of inventors were more likely to find their way into the ODNB for reasons other than the success of their inventions; the gentry category, for example, includes several Earls, who were naturally more likely to be included in ODNB, while manufacturers could make it in for building up large and successful firms. We can see this reflected in the data. I have also digitized the text of the matched ODNB biographies and undertaken a text analysis. This shows that “patent” appears in 81 percent of the matched biographies for engineers but only 68 percent of matched biographies for non-engineers. Similarly, “invent” appears in 70 percent of the biographies for engineers but only 53 percent for non-engineers.

Table 30 presents regression results where the data set are those inventors with 2+

⁶³In a small number of cases the year of baptism is used in place of the year of birth because the year of birth is not reported in the ODNB.

	Inventors with ≥ 2 patents	Inventors in ODNB database	Inventors in ODNB born by 1780	Inventors in ODNB born after 1780
Engineers	220 15.5%	56 26.9%	17 18.1%	39 34.2%
Manufacturers	584 41.1%	54 26.0%	20 21.3%	34 29.8%
Gentlemen & Esquires	300 21.1%	46 22.1%	26 27.7%	20 17.5%

Table 29: Appearances in the ODNB data by broad occupation group

Includes only inventors with a unique modal occupation. The percentages in the first column reflect each occupation group's share of total inventors searched for in the ODNB (those with ≥ 2 patents). The percentages in the second column are the shares of inventors from each occupation group found in the ODNB relative to all inventors found in the ODNB. The shares in the last two columns are the shares of inventors from each occupation group found in the ODNB born before or after 1780, relative to all inventors found in the ODNB born before or after 1780.

patents who were searched for in the ODNB and the outcome variable is an indicator for whether the inventor was found in the ODNB. Since this outcome is an indicator variable, I run both OLS and Probit regressions. As explanatory variables, I focus on whether the modal occupation associated with each name was engineering. In Columns 2, 4, and 6 I control for the actual number of patents associated with each name.

The results in Table 30 indicate that engineers were more likely to end up in the ODNB, even conditional on the number of patents filed. In terms of magnitudes, focusing on the results from the linear probability models in Columns 1-2 we can see that the chances an individual is in the ODNB increases by just over 6 percentage points if they are an engineer, or over 9 percentage points if I do not control for the number of patents that they produced. These are large differences relative to the sample mean of 12.8%.⁶⁴ This much greater probability suggests that the technologies that engineers were producing were more impactful than those produced by other types of inventors, even after controlling for the fact that they were, on average,

⁶⁴This sample mean differs from the 11.9% of inventors with 2+ patents found in the ODNB because it includes only inventors with a unique modal occupation.

DV: Indicator for being in the ODNB						
	OLS regressions				Probit (marginal effect)	
	(1)	(2)	(3)	(4)	(5)	(6)
Engineers	0.0948*** (0.0254)	0.0575** (0.0244)	0.0808*** (0.0262)	0.0393 (0.0253)	0.075*** (0.0252)	0.0351 (0.0226)
Manufact.			-0.0374** (0.0149)	-0.0472*** (0.0146)	-0.0397** (0.0155)	-0.0457*** (0.0149)
No. of patents		0.0325*** (0.00467)		0.0330*** (0.00470)		0.0215*** (0.0029)
Observations	1,987	1,987	1,987	1,987	1,987	1,987
R-squared	0.010	0.069	0.013	0.073		

Table 30: Regression results using ODNB data

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. Engineers and manufacturers are identified based on unique modal occupation. Inventors without a unique modal occupation are not included.

producing more inventions than other types of patentees. As expected, filing more patents is also strongly associated with the chance that an individual ends up in the ODNB. Inventors with manufacturing occupations, in contrast, were less likely on average to end up in the ODNB (gentlemen, esquires, and other types of inventors fell in between).

I have also digitized the text of the ODNB biographies for all of those inventors in the matched patent-ODNB data. One thing that we can look at in the ODNB biographies is the length allocated to each inventor. This provides an additional way to quantify the prominence of the various inventors, since more important individuals are granted more extensive biographies. The length of the ODNB biographies in my matched data set range from 188 words (Joseph Clinton Robertson) to 9,968 (James Watt), with a mean length of 1,208 words. There is a clear correlation with the importance of each inventor. The top five engineers, by word count, are Watt, George Stephenson (4,897), Richard Trevithick (3,126), Charles William Siemens (2,934), and Henry Bessemer (2,924).⁶⁵ While one could naturally argue about whether any

⁶⁵After Watt, the next longest articles are on Thomas Cochrane, Earl of Dundonald, the Naval

particular inventor receives the space (and appreciation) that they deserve, in broad strokes this statistic seems informative.

Table 31 presents the average word count per inventor by occupation group. We can see that engineers typically have longer articles than others, with the exception of Gentlemen and Esquires. This suggests that, even conditional on being included in the ODNB, engineers may have been more successful than other types of inventors.

Occupation	Avg. words	Occupation	Avg. words
Agric., food/drink makers	699	Manufacturing	954
Construction/millwrights	992	Merchant	1,162
Engineering	1,323	Other occ.	752
Esquire	1,112	Prof. services	997
Gentry	1,378	Unknown	1,563

Table 31: Words per article by inventor type

hero, followed by Henry Seymour Conway, a cousin of Walpole who rose to be Commander in Chief and played an important role in the American Revolution.

E.9 Coinventor teams and patent quality

In the main text, I showed that engineers were more likely to file patents with coinventors than other types of inventors. In this appendix, I look at whether inventors working in teams produced higher quality inventions using the two measures of quality that I observe at the patent level.

In the first set of results, in Table 32, I use the patent quality index from Nuvolari *et al.* (2021).⁶⁶ For this analysis the data are organized at the patent level and the dependent variable is the BCI quality index for the patent. The key independent variable is either the number of inventors, or an indicator for whether the patent had more than one inventor (most patents had just one during this period). I am also interested in whether this effect depends on whether one of the team members was an engineer. To study this, I interact either the number of inventors or the flag for multi-inventor patents with an indicator for whether any of the team members listed their occupation as engineer.⁶⁷

The results in Columns 1-2 of Table 32 show that patent quality is increasing in the number of coinventors on the patent. Column 3 shows analogous results using a discrete indicator for whether the patent had more than one inventor. These findings suggest that patents produced by teams were of higher quality than those produced by individual inventors.

In Columns 4-6, I look at whether these effects differed depending on whether one of the inventors in the team was an engineer. Across all three of these specifications, I find that the benefits of working in teams are driven entirely by teams that include at least one engineer.

In the second set of results, in Table 33, I measure patent quality based on whether a patent was renewed after either three or seven years. As described in the main text, renewals provide a strong measure of patent quality, but one that is only available for patents filed toward the end of my study period. For this analysis, I organize my data at the patent level, and the dependent variable is an indicator for whether a fee was paid to renew that patent at either three or seven years. The main explanatory

⁶⁶Using the quality index in Nuvolari & Tartari (2011) generates very similar results.

⁶⁷Very similar results are obtained if I instead use an indicator for whether any inventor had engineer as their modal occupation.

DV: Patent quality based on the BCI index						
	(1)	(2)	(3)	(4)	(5)	(6)
Num. inventors	0.0120*	0.0115*		-0.00452	-0.00483	
	(0.00688)	(0.00691)		(0.00679)	(0.00683)	
Multi-inventor pat.			0.0167*			-0.00392
			(0.00924)			(0.00856)
Num. inventors x engineer				0.0590***	0.0599***	
				(0.00812)	(0.00863)	
Multi-inventor pat. x engineer						0.0947***
						(0.0291)
Year FE		Yes	Yes		Yes	Yes
Observations	11,243	11,243	11,243	11,243	11,243	11,243
R-squared	0.000	0.028	0.028	0.008	0.036	0.030

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 32: Impact of coinventors on patent quality using the BCI index

variable is either the number of inventors or an indicator for whether the patent had multiple inventors. I also interact these variables with an indicator for whether any team member listed their occupation as engineer.

Panel A of Table 33 looks at results where the outcome variable is an indicator for whether a patent was renewed after three years. Columns 1a and 2a show that patents with multiple inventors were more likely to be renewed. Columns 3a and 4a show that these effects are much stronger if at least one of the inventors is an engineer. Panel B shows that similar results are obtained when using renewal at seven years as the quality measure. Though the advantage of teams that include an engineer over other teams is somewhat smaller when using renewal at year seven, the results in Columns 3b suggest that the effect of having one more team member is still almost twice as large if one of the team members is an engineer.

Panel A	DV: Indicator for patent renewed at year three			
	(1a)	(2a)	(3a)	(4a)
Num. inventors	0.0185*** (0.00417)		0.0108** (0.00429)	
Multi-inv. pat.		0.0197*** (0.00520)		0.0129** (0.00580)
Num. inventors x engineer			0.0276*** (0.00389)	
Multi-inv x engineer				0.0274** (0.0112)
Observations	37,817	37,817	37,817	37,817
Panel B	DV: Indicator for patent renewed at year seven			
	(1b)	(2b)	(3b)	(4b)
Num. inventors	0.0145*** (0.00317)		0.0121*** (0.00325)	
Multi-inv. pat.		0.0145*** (0.00376)		0.0144*** (0.00421)
Num. inventors x engineer			0.00945*** (0.00283)	
Multi-inv x engineer				0.000469 (0.00814)
Observations	33,480	33,480	33,480	33,480

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Renewal at year three is available for patents filed from 1855-1869. Renewal at year seven is available for patents filed from 1853-1865. As a result, the number of observations used in Panel A differ from the number used in Panel B.

Table 33: Impact of coinventors on patent quality based on renewals

E.10 Analyzing the make-up of coinventor teams

In this appendix I examine the composition of teams of coinventors and how these differ for inventors within broad occupation groups. These patterns can be viewed in Table 34, where I separate engineers, those with manufacturing occupations, gentlemen and esquires, and all others. The way to read this table is as follows. Each cell reflects the share of multi-inventor patents including one or more inventors from the row occupation and the column occupation, divided by the total number of multi-inventor patents filed by inventors in the row occupation. Thus, the values sum to (close to) one looking across the row, with the discrepancy due to the fact that some multi-inventor patents have more than two inventors.

Looking across the top row, the first cell reflects the share of multi-inventor patents by engineers that include one or more other engineers as coinventors. The second cell of the first row reflects the share of multi-inventor patents by engineers that include one or more manufacturers as coinventors, relative to the total number of multi-inventor patents by engineers, and so on.

		Coauthoring with:			
		Engineers	Manufact.	Gentl/Esq.	Others
Patents by:	Engineer	0.419	0.215	0.215	0.234
	Manufacturer	0.081	0.596	0.137	0.247
	Gentry/Esq.	0.196	0.330	0.265	0.271
	Other	0.133	0.372	0.170	0.546

Table 34: Make-up of coinventor teams by inventor type

See text for details of the construction of these figures.

There are a couple of intriguing patterns to notice in this table. First, those with manufacturing occupations were much more likely to coauthor with other manufacturers than engineers were to coauthor with other engineers. In part, this may reflect that there were, overall, more other manufacturers to coauthor with, but it also hints at the possibility that because manufacturers were more focused on technologies related to their specific industries, they were more likely to coauthor with

others working in that industry. In contrast, looking across the top row shows that engineers are often found to be working with inventors from other groups. This may reflect, for example, partnerships between engineers and manufacturers or gentlemen who could contribute financing or political connections to a project. This pattern is even more pronounced for Gentlemen and Esquires, a group that regularly patents with every other group.

E.11 Additional within-inventor regression results

Table 35 presents some additional within-inventor regression results. Specifically, these regressions include quadratic controls on time since first patent. In all cases, the estimated effect of becoming an engineer is even stronger than that reported in the main text.

	DV: Share of patents with multiple inventors			DV: Patents per year		
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.0585** (0.0237)	0.0581** (0.0236)	0.0896*** (0.0305)	0.278*** (0.0339)	0.294*** (0.0380)	0.0919** (0.0373)
Years since first patent	0.000639 (0.00128)	0.00116 (0.00170)	0.00109 (0.00170)	-0.00847*** (0.00196)	-0.0304*** (0.00339)	-0.0302*** (0.00351)
Years since first, squared	-5.30e-05 (4.24e-05)	-8.62e-05 (9.15e-05)	-7.87e-05 (9.08e-05)	0.000194*** (7.14e-05)	0.00136*** (0.000202)	0.00139*** (0.000211)
Years since first, cubed		3.98e-07 (1.21e-06)	4.03e-07 (1.17e-06)		-1.26e-05*** (2.31e-06)	-1.29e-05*** (2.41e-06)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Dropping first year as Eng.			Yes			Yes
Observations	5,333	5,333	5,152	18,787	18,787	18,641
R-squared	0.548	0.548	0.552	0.238	0.248	0.247

Table 35: Within-inventor regressions robustness

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by individual. The Engineer variable is an indicator for each individual that takes a value of one starting from the first year in which an individual listed their occupation as engineer in a patent, and zero otherwise.

E.12 Distribution of engineer patents across tech. categories

Table 36 lists the technology categories where engineers made up the largest fraction of patentees. Table 37 lists the technology categories that accounted for at least 2% of all patents by engineers in the 1700-1849 period. Both of these show that engineers played an important role in key Industrial Revolution technologies, including machine tools, steam engines, railroads, etc. However, we can also see that engineers were fairly diverse in the types of technologies in which they patented. Clearly, they were not a group that was working in just one or a small number of technology types.

Technology category	Share by Engineers
Boring, Drilling, Punching	0.622
Steam; Steam-Engines and Boilers.	0.517
Boilers and Pans	0.484
Railways and Railway Rolling-Stock	0.419
Gas Manufacture and Consumption	0.400
Bridges, Arches, Viaducts, Aqueducts	0.356
Air and Wind: Air and Gas Engines and Windmills	0.351
Turning	0.333
Tunnels, Excavations, And Embankments	0.286
Smoke Prevention. -Consumption Of Fuel	0.284
Measuring And Numbering	0.283
Motive Power and Propulsion	0.282
Casks And Barrels	0.280

Table 36: Technology categories with a high share of patents from Engineers

This table lists the share of patents within a technology category with “engineer” listed as the occupation, excluding communicated patents. Data cover 1700-1849.

Technology category	Patents	Share of engineer patents
Steam-Engines And Boilers	444	0.148
Motive-Power And Propulsion	238	0.080
Railways And Railway Rolling-Stock	207	0.069
Smoke Prevention -Consumption Of Fuel	125	0.042
Water And Fluids	112	0.037
Boilers And Pans	93	0.031
Metals And Metallic Substances	90	0.030
Gas Manufacture And Consumption	86	0.029
Spinning And Preparing For Spinning	86	0.029
Fireplaces, Stoves, Furnaces, Ovens, And Kilns	85	0.028
Heat, Heating, Evaporating, And Concentrating	73	0.024
Coaches And Other Road Conveyances	66	0.022
Ship-Building, Rigging, And Working	65	0.022
All others	1221	0.408

Table 37: Top technology categories for patents by Engineers

This table lists the share of patents with “engineer” listed as the occupation represented by each technology category, for those categories that accounted for at least 2% of patents by engineers, excluding communicated patents. Data cover 1700-1849.

E.13 Number of technology categories per inventor regressions

Table 38 presents regression results looking at how the number of technology categories patented in varies by inventor type. The results in the first column, which use data from the full sample period, show that engineer inventors patented in more technology categories than other types of inventors, while manufacturer-inventors patented in fewer categories. These results are not driven by the fact that engineers are concentrated toward the latter part of the sample. Columns 2-5 show that similar patterns are also observed in every two-decade sub-period from 1770-1849.

DV: Number of technology categories per inventor					
	All years	1770- 1789	1790- 1809	1810- 1829	1830- 1849
	(1)	(2)	(3)	(4)	(5)
Engineer	0.824*** (0.0916)	2.437*** (0.904)	0.855*** (0.302)	0.534*** (0.153)	0.705*** (0.109)
Manufacturer	-0.125*** (0.0322)	-0.0302 (0.0805)	-0.100 (0.0658)	-0.165*** (0.0614)	-0.130** (0.0518)
Observations	7,917	648	1,204	1,789	4,195
R-squared	0.031	0.089	0.030	0.022	0.025

Table 38: Number of technology categories per inventor regressions

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parenthesis. The unit of observation is an inventor. The outcome variable is the number of different technology categories that the inventor patented in across all years (Column 1) or within 20-year periods (Columns 2-5). The explanatory variable is an indicator for whether the inventor's modal occupation is engineer. Inventors without a unique modal occupation are not included. Data cover 1700-1849.

E.14 Technology categories per inventor using ODNB-identified engineers

Table 39 presents results looking at the number of technology categories patented in by engineers vs. other types of inventors, but identifying engineers using information from the ODNB rather than the self-reported occupations from the patent data. All of these results start with a sample of all individuals classified as active in science, technology, engineering or manufacturing in the ODNB which are then linked to the patent data. In Column 1, engineers are identified based on the classifications provided by the ODNB, which are based on the judgement of modern historians. In Columns 2-4, I use the predicted probability that someone is likely to be an engineer based on the verb stems included in their ODNB biography, as described in Section 2. In Column 2, engineers are those with a predicted score that is more than 1 s.d. above the mean score. In Column 3, I use a higher cutoff of 1.5 s.d. In Column 4, I use the continuous score. Across all of these specifications, we see evidence suggesting that engineers patented across more technology categories than other types of inventors classified as working in science, technology, engineering or manufacturing in the ODNB. In most of these results, this relationship is statistically significant at

DV: Technology categories per inventor				
Engineers identified by:	ODNB occ. (historians)	Predicted based on verb stems in bio		
		1 s.d. cutoff	1.5 s.d. cutoff	Continuous
	(1)	(2)	(3)	(4)
Engineer	0.710*** (0.243)	0.978** (0.444)	0.910 (0.698)	0.645* (0.362)
Constant	2.095*** (0.117)	2.229*** (0.107)	2.275*** (0.105)	2.099*** (0.138)
Observations	594	594	594	594
R-squared	0.017	0.012	0.006	0.012

Table 39: Technology categories per inventors using ODNB-based and predicted engineers

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Robust standard errors in parentheses. The unit of observation in this analysis is the patent. The sample includes all patents linked to individuals in the ODNB listed as working in science, technology, manufacturing or engineering. In Column 1, engineers are identified based on whether they were classified as an engineer by the historians who produced the ODNB. In Columns 2-4, engineers are identified using the predicted probability that an individual was an engineer based on the procedure described in Section 2, with individuals with scores of 1 or 1.5 s.d. above the average classified as engineers in Columns 2 and 3, respectively, and the continuous measure used in Column 4.

the 90% or 95% level, except in Column 3, where the high cutoff means that the effect is being identified off of a relatively small number of predicted engineers, resulting in larger standard errors.

E.15 Alternative Billington-Hanna technology category data

This section looks at whether the results using the technology category data are robust to using an alternative set of technology categorizations. As an alternative to the BPO categorizations, I use a machine-learning based classification generated by Billington & Hanna (2018) using the text of patent titles to allocate patents into 20 categories. In the analysis below, I use their “TopicOne” categorization, though similar results are also obtained from their “TopicTwo” categorization.

Table 40 presents a breakdown showing the average number of Billington-Hanna technology categories that individual inventors in each occupation group patented in. We can see from this table that in general inventors were substantially less likely to be active in multiple Billington-Hanna technology categories, a natural consequence of the fact that there are far fewer categories than in the British Patent Office classification. However, we also see that engineers are, on average, active in more technology categories than any other group. The regression results in Table 41 confirm that this difference is statistically significant across the full sample period as well as every twenty-year sub-period from 1770.

Occupation group	Avg. number of tech. categories per inventor	Occupation group	Avg. number of tech. categories per inventor
Agric., food/drink makers	1.144	Merchant	1.153
Chemical manuf.	1.288	Metals and mining	1.228
Construction	1.127	Misc. manuf.	1.183
Engineering	1.570	Other occ.	1.144
Esquire	1.376	Prof. services	1.196
Gentry	1.304	Textiles	1.134
Machinery and tool manuf.	1.207	Unknown	1.079

Table 40: Average Billington-Hanna technology categories per inventor, by occupation type

Based on the modal occupation group of each inventor. Inventors without a unique modal occupation group are not included. Excludes patents that are communications.

DV: Number of technology categories per inventor					
	All years (1)	1770- 1789 (2)	1790- 1809 (3)	1810- 1829 (4)	1830- 1849 (5)
Engineer	0.363*** (0.0447)	0.559* (0.317)	0.470*** (0.144)	0.236*** (0.0864)	0.334*** (0.0547)
Manuf.	-0.0121 (0.0152)	-0.00736 (0.0346)	-0.00685 (0.0347)	-0.0499 (0.0380)	0.0104 (0.0236)
Observations	7,964	652	1,210	1,803	4,213
R-squared	0.023	0.028	0.030	0.010	0.020

Table 41: Number of Billington-Hanna technology categories per inventor regressions

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parenthesis. The unit of observation is an inventor. The outcome variable is the number of different technology categories that the inventor patented in across all years (Column 1) or within 20-year periods (Columns 2-5). The explanatory variable is an indicator for whether the inventor’s modal occupation is engineer. Inventors without a unique modal occupation are not included.

F Results linking scientific articles to patents

Table 42 presents a breakdown of the author-inventors who generated articles in either the *Proceedings* (top panel) or *Transactions* (bottom panel) and also matched to one or more patented inventions.⁶⁸ These scientist-inventors are broken down into occupation groups based on the occupations listed in the patent data following the categorizations used in my main analysis, except that chemists and medical doctors are broken out separately.

The top two rows in both panels of Table 42 show that most of the authors of scientific studies that were also engaged in patenting activities fall into two groups: engineers and gentlemen/esquires, the latter group comprised mainly of individuals from the aristocratic classes. Together, these two groups constitute about 40-50% of the “bridge” between science and engineering. Medical doctors, chemists, and the “other professionals” group, which mainly includes professors, lawyers, and clergy, also played an important role. It is notable that there are very few manufacturers who were involved in both science and technology, particularly since manufacturers

⁶⁸Additional information about the Proceedings and Transactions data can be found in Hanlon (2022).

were the largest occupation group within the patent data. Of the small number of manufacturer-inventors that also produced scientific articles, almost all were manufacturers of instruments or timepieces. The importance of engineers and gentlemen/esquires is even more pronounced in the first two rows of Panel B, which focuses on the more exclusive group of authors with articles published in the *Transactions*.

The middle rows in Panel A show that engineers accounted for an even larger share, 46%, of the patents generated by individuals who were also involved in scientific pursuits. This is a much larger share than any other group. This is because engineers generated, on average, more than eight patents each, more than double the number of any other group. However, while engineers generated far more patents per person than other authors, the bottom rows of Panel A show that they tended to generate fewer scientific articles than gentlemen, chemists, or other professionals such as professors and lawyers. Thus, relative to other types of scientist-inventors, engineers appear to have been relatively more specialized in technology development while dabbling in science, while others appear more specialized in science while dabbling in technology development. Panel B shows that these patterns are, if anything, even stronger when we focus only on authors of articles published in the *Transactions*. Thus, the overriding message from this table is that one group, engineers, played a key role in bridging science and technology during the first few decades of the nineteenth century.

A. Proceedings authors with a patent							
	Total	Engineers	Gentlemen/Esq.	Manuf.	Doctors	Chemists	Other prof.
Authors	132	28	24	9	19	16	11
Share		0.21	0.18	0.07	0.14	0.12	0.08
Patents	520	241	64	37	34	52	28
Share		0.46	0.12	0.07	0.07	0.10	0.05
Patents per author		8.61	2.67	4.11	1.79	3.25	2.55
Articles	561	90	121	19	53	182	96
Share		0.16	0.22	0.03	0.09	0.32	0.17
Articles per author		3.21	5.04	2.11	2.79	11.38	8.73
B. Transactions authors with a patent							
	Total	Engineers	Gentlemen/Esq.	Manuf.	Doctors	Chemists	Other prof.
Authors	75	16	16	4	7	8	8
Share		0.21	0.21	0.05	0.09	0.11	0.11
Patents	304	155	42	22	14	18	13
Share		0.51	0.14	0.07	0.05	0.06	0.04
Patents per author		9.69	2.63	5.50	2.00	2.25	1.63
Articles	233	42	76	8	18	38	51
Share		0.18	0.33	0.03	0.08	0.16	0.22
Articles per author		2.63	4.75	2.00	2.57	4.75	6.38

Table 42: Breakdown of authors and patents by occupation group

G Evidence on the licensing and sale of patents

Table 43 describes the share of litigated patents that were assigned or licensed using data from Bottomley (2014). We can see that the rate at which patent rights were being transferred is quite high. Patent holders used a variety of methods to transfer patent rights, including full assignment, partnerships, and licensing.

Table 44 breaks these patterns down by occupation group. Note that the totals will not add up to those in Table 43 because these results are at the inventor level, and more than one inventor may be involved in producing a patent. This table shows that, relative to other groups, and particularly relative to manufacturers, engineers were quite likely to transfer some or all of their patent rights through the various available methods.

Period	Patents litigated	Transferred		Assigned in full		Partnership		Licensed	
		Num.	Share	Num.	Share	Num.	Share	Num.	Share
1770-1829	95	51	54%	28	29%	30	32%	19	20%
1830-1849	148	93	63%	45	30%	54	36%	38	26%

Table 43: Transfers of patent rights among litigated patents, 1770-1845

Data from Bottomley (2014).

Period	Patents litigated	Transferred		Assigned in full		Partnership		Licensed	
		Num.	Share	Num.	Share	Num.	Share	Num.	Share
Engineers	34	23	68%	7	21%	12	35%	11	32%
Manufacturers	124	68	55%	27	22%	48	39%	18	15%
All others	96	67	70%	36	38%	41	43%	30	31%

Table 44: Transfers of patent rights by occupation group, 1770-1845

Data from Bottomley (2014). Occupation groups are identified using the modal occupation of individuals appearing in the patent data. Individuals without a unique modal occupation are excluded. Note that the sum of the various transfer methods exceeds the total number of patents transferred because patent rights could be transferred using more than one method.

H Analyzing inventors' backgrounds

Using patent data that has been manually matched to ODNB biographies, it is possible to extract biographical information on the background of patenting inventors. To do so, I began with all individuals responsible for at least two patents in my main study period (1700-1849) and attempted to manually match each to the ODNB. Out of the 2,052 inventors with two or more patents searched for, I find 245 matches, a match rate of 11.9%. This approach allows a fair comparison between the backgrounds of inventors in different occupations groups, where occupation is identified based on the patent data definition.

I focus on the type of education each inventor had based on a manual review of the biographical information in the ODNB. This can shed light on the extent to which engineers differed from other types of inventors in terms of their educational background, though of course it is important to remember that this is a selected sample of only the most successful inventors.

Table 45 describes the share of inventors in the matched ODNB data with each type of educational background broken down by occupational group (based on the modal occupation listed for each inventor). The categories I focus on are university education, apprenticeship, a purely working background (beyond basic primary schooling), private pupillage, learning through working in a family business, and whether the individual attended a grammar or boarding school (as opposed to a village or smaller private school). Note that these shares do not need to add up to one since for some the background is unknown and for others they may have taken advantage of more than one option (e.g., an apprenticeship and then university).

As a starting point, it is notable that the overall patterns shown in Table 45 bear a great deal of similarity to patterns reported in previous studies based on biographical sources. For example, Meisenzahl & Mokyr (2012) find a university attendance rate of 15%, while Howes (2017) finds a rate of 18%. The top row of Table 45 shows that the rate among my matched patent-ODNB data is 17.3%. For apprenticeships, Meisenzahl & Mokyr (2012) report a rate of 40% while 31% of the inventors in the expanded databases used by Howes (2017) were apprenticed. The rate in my data is very similar to Howes', at 27%. Howes (2017) also finds that 8% of his inventors were

private pupils, which is similar to the 9.6% in my data. These similarities provide an indicator that the overall patterns identified in the set of patentees I focus on are similar to those found among the prominent inventor samples used in previous studies.

In the first column of Table 45, we see that engineers were, if anything, less likely to have attended university than other types of inventors except manufacturers. Gentlemen and the “other” category (which included a number of doctors) were more likely to have attended university. However, for those engineers that did spend time at university, it was almost always at a Scottish university, particularly Edinburgh, whereas most of the university attendees in other groups attended Oxford or Cambridge.

The most common educational background for engineers was an apprenticeship. In this, they were similar to inventors who listed a manufacturing occupation. Engineers were also substantially more likely to have a purely working background, which almost always meant that they were mainly self-taught in their spare time. The remaining columns show that engineers were just slightly more likely to have been a private pupil, and they were much less likely to have learned through working in a family business than manufacturers. Finally, engineers were less likely to have attended a grammar, boarding, or higher-end private school than other types of inventors, though their rate was similar to manufacturers. This is perhaps not surprising given that these schools often favored teaching Latin and Greek over more practical mechanical skills.

	University	Apprenticed	Working	Private pupillage	Family business	Grammar/boarding sch.
All	0.173	0.274	0.096	0.096	0.183	0.212
Engineers	0.107	0.375	0.143	0.125	0.179	0.125
Gentl/Esq.	0.196	0.196	0.065	0.109	0.109	0.326
Manufact.	0.111	0.333	0.074	0.056	0.315	0.111
Others	0.288	0.173	0.096	0.096	0.115	0.308

Table 45: Educational background of different types of inventors from ODNB data

Inventors are classified based on their modal occupation. Inventors without a unique modal occupation are not included.

A natural question about the patterns shown in Table 45 is whether the differ-

ences across occupations are due to differences in the period in which most of the inventors in a particular group were born. To examine this, Table 46 breaks down the education results based on the date of birth of each individual (which is reported in the ODNB for almost all of the matched inventors). Perhaps surprisingly, this reveals that the overall share of inventors coming from each type of background was fairly stable over time. However, among engineers, we see a much higher share of inventors with a working background among those born before 1750, while the importance of apprenticeships rises over time from 25% for those born before 1750 to 48% for those born after 1800. In contrast, among manufacturers, the share apprenticed was declining over time, replaced mainly by a rising share trained within the family business or as private pupils. University education rose among engineers, from zero before 1750 to 19% for those born after 1800, and a similar increase is observed among manufacturers.

Born before 1750							
	No inventors	Univ.	Appr.	Working	Private pupillage	Family business	Grammar/ boarding sch.
All	34	0.235	0.235	0.147	0.059	0.206	0.265
Engineers	4	0.000	0.250	0.500	0.000	0.250	0.250
Gentl/Esq.	8	0.250	0.125	0.250	0.125	0.125	0.375
Manufact.	6	0.000	0.667	0.000	0.000	0.333	0.333
Others	16	0.375	0.125	0.063	0.063	0.188	0.188

Born from 1750-1800							
	No inventors	Univ.	Appr.	Working	Private pupillage	Family business	Grammar/ boarding sch.
All	117	0.128	0.282	0.085	0.085	0.171	0.214
Engineers	31	0.065	0.323	0.129	0.065	0.194	0.097
Gentl/Esq.	24	0.167	0.208	0.000	0.167	0.125	0.375
Manufact.	32	0.094	0.344	0.094	0.031	0.250	0.094
Others	30	0.200	0.233	0.100	0.100	0.100	0.333

Born 1800 or later							
	No inventors	Univ.	Appr.	Working	Private pupillage	Family business	Grammar/ boarding sch.
All	57	0.228	0.281	0.088	0.140	0.193	0.175
Engineers	21	0.190	0.476	0.095	0.238	0.143	0.143
Gentl/Esq.	14	0.214	0.214	0.071	0.000	0.071	0.214
Manufact.	16	0.188	0.188	0.063	0.125	0.438	0.063
Others	6	0.500	0.000	0.167	0.167	0.000	0.500

Table 46: Educational background of different types of inventors from ODNB data by period

Inventors are classified based on their modal occupation. Inventors without a unique modal occupation are not included.

I Analysis of French patent data

In this appendix, I look at whether engineers (ingénieure) in France differed from other inventors, as they did in Britain. As a starting point, Table 47 presents averages of patents per inventor, the length of patent term per inventor, and the number of technology categories per inventor, for different occupation groups. These results reveal that engineers filed more patents than any other occupation group, they filed

Occupation group	Avg. patents per person	Avg. length of patent term (years)	Avg. number of tech. categories
Ag/Food/Drink	1.17	7.65	1.10
Chemical	1.33	8.52	1.23
Construction	1.15	7.27	1.10
Engineer	2.29	9.72	1.91
Machinery, tools	1.31	6.85	1.11
Mechanic	1.42	7.66	1.27
Merchant	1.18	8.57	1.11
Metals/Mining	1.21	8.05	1.13
Military	1.32	8.72	1.18
Misc. manufacture	1.26	7.14	1.12
Other	1.22	8.45	1.13
Professional	1.25	8.61	1.16
Public/Education	1.44	8.35	1.28
Textiles	1.25	7.49	1.07
Unknown	1.41	8.98	1.29

Table 47: Average characteristics by occupation group in France

patents with longer terms on average than any other occupation group, and they patented in more technology categories than any other occupation group.

Table 48 analyzes these patterns in a regression framework. Column 1 shows that engineers filed more patents per person than other types of inventors, while manufacturer-inventors filed fewer patents.⁶⁹ As I will discuss later, some of the engineers that patented in the French data were based in Britain. To ensure that these British inventors are not driving the results, Column 2 presents results in which any inventor declaring an address in the U.K. in any of their patents is excluded.

Columns 3-4 conduct a similar exercise looking at the average length of the patent term applied for by different types of inventors. This is interesting because it may be an indicator of the ex ante assessment of the quality of an invention, though it should be considered with caution because it may also be influenced by factors such as credit constraints. The results in Column 3 (all inventors) and Column 4 (excluding British inventors) indicate that engineers applied for significantly longer patent terms than other types of inventors, suggesting that they may have been producing higher-quality

⁶⁹As in the British patent analysis, the manufacturer-inventor category includes those working in machinery and tools, metals and mining, chemicals, textiles, and misc. manufacturing.

innovations. Columns 5-6 of Table 48 show that engineers in France also filed patents across a wider range of technology categories than other types of inventors.

Thus, my analysis of the French patent data confirms the main patterns found in the British patent data: engineers were more productive in terms of the number of patents they produced, there is evidence suggesting that they also produced higher quality patents, and they also patented across a broader set of technology categories. Moreover, not only were engineers more productive than the average non-engineer inventor, they were also more productive than every other occupation group.

	Patents per person		Avg. length of patent term		Tech. categories per person	
	All inventors	Excluding UK-based	All inventors	Excluding UK-based	All inventors	Excluding UK-based
Engineer	0.965*** (0.147)	0.838*** (0.137)	1.156*** (0.204)	1.045*** (0.218)	0.690*** (0.108)	0.594*** (0.0993)
Manuf.	-0.0589*** (0.0179)	-0.0589*** (0.0181)	-1.195*** (0.0736)	-1.047*** (0.0740)	-0.0954*** (0.0201)	-0.0949*** (0.0212)
Observations	10,556	9,980	10,541	9,967	10,557	9,981
R-squared	0.032	0.025	0.031	0.026	0.011	0.008

Table 48: Differences between engineers and other patentees in France

Robust standard errors in parenthesis. Occupations are based on the modal occupation of each inventor. Inventors without a unique modal occupation group are not included.

Figure 8 plots the share of French patents by different occupation groups. Two patterns are notable here. First, the overall distribution of patents changes very little across the study period, with the exception of a mild decline in patents by “other” occupations, those that are essentially unclassifiable. We see no evidence of the rise of engineering as an important part of the innovation system, nor do any other occupation groups show substantial increases. Second, the main group of inventors by far across the period are manufacturer-inventors, particularly those in the miscellaneous manufacturing category, which includes a diverse set of manufacturer-inventors: glass makers, makers of shoes and hats, etc. Overall, the French patent system remained fairly stable across the study period and dominated by manufacturer-inventors, much as the British system was in the middle of the 18th century, before the emergence of

professional engineers.

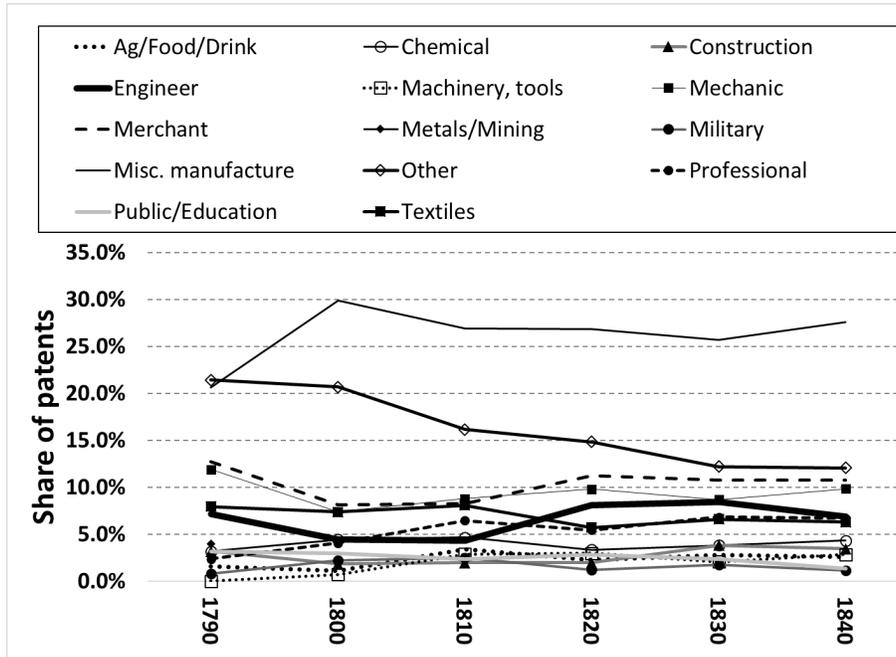


Figure 8: Share of French patents by occupation groups

J Civil engineering appendix

This appendix provides some additional detail supporting the analysis of civil engineering in Section 8. Figure 9 describes the number of major infrastructure projects on Skempton's list in each decade as well as the estimated cost (in current dollars) of those works. We can see from this graph that, while there was some growth in the number of projects in the first half of the 18th century, the major increase started between 1750 and 1770. While it is difficult to determine the direction of causality, it seems likely that the increase in the demand for civil engineering work described in Figure 9 provided an increase in market size that was sufficient to allow individuals to begin specializing as civil engineers.

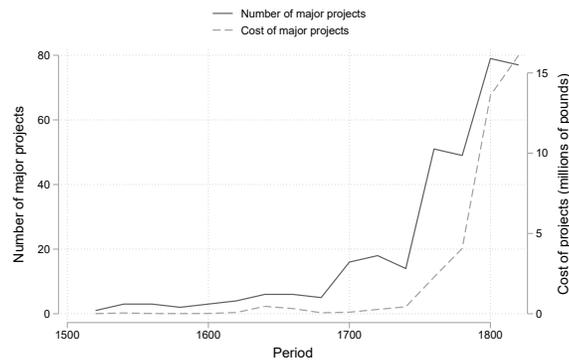


Figure 9: Number and cost of major civil engineering works, 1500-1830

Source: Skempton *et al.* (2002) Appendix II.

Table 49 provides a breakdown of the main types of infrastructure projects that took place in each period. From 1500-1700, the most important types of projects, in terms of numbers or cost, related to harbors and drainage works. The large expenditures on drainage in the first half of the 17th century reflects the Great Level drainage project of the Fen marshlands. River navigation improvements were also important during this period, as were occasional bridge and water supply construction projects. From 1750-1799, however, the pattern changed due to the enormous canal building boom that took place. Canal building continued after 1800, but at a slower pace,

Share of projects								
Period	Canals	River Nav.	Drainage	Harbors	Railways	Water supply	Bridges	Other
1500-1549	0.00	0.20	0.00	0.60	0.00	0.00	0.20	0.00
1550-1599	0.20	0.00	0.20	0.40	0.00	0.20	0.00	0.00
1600-1649	0.00	0.25	0.50	0.00	0.00	0.08	0.17	0.00
1650-1699	0.13	0.17	0.17	0.26	0.00	0.22	0.00	0.00
1700-1749	0.08	0.17	0.11	0.28	0.03	0.06	0.11	0.08
1750-1799	0.41	0.12	0.09	0.12	0.03	0.00	0.18	0.04
1800-1830	0.17	0.04	0.04	0.29	0.10	0.00	0.25	0.04

Share by cost (where cost estimates are available)								
Period	Canals	River Nav.	Drainage	Harbors	Railways	Water supply	Bridges	Other
1500-1549	0.00	0.02	0.00	0.82	0.00	0.00	0.16	0.00
1550-1599	0.11	0.00	0.18	0.70	0.00	0.01	0.00	0.00
1600-1649	0.00	0.15	0.73	0.00	0.00	0.06	0.06	0.00
1650-1699	0.09	0.07	0.36	0.48	0.00	0.00	0.00	0.00
1700-1749	0.14	0.17	0.04	0.26	0.01	0.00	0.31	0.02
1750-1799	0.84	0.04	0.03	0.05	0.03	0.00	0.04	0.00
1800-1830	0.24	0.03	0.03	0.43	0.06	0.00	0.11	0.04

Table 49: Share of major civil engineering projects, by type and period

Source: Skempton *et al.* (2002) Appendix II.

while we can begin to see the start of the railway boom that gathered steam after 1830.

Figure 10 describes the share of major British civil engineering projects that were the first major project undertaken by the chief engineer (open diamond symbols). From 1600-1760, roughly 75% of major engineering projects were overseen by someone who had not previously overseen another major project. The only major exception to this is in 1640-1659, when the Dutchman, Cornelius Vermeyden, oversaw several important drainage works. It is notable that this pattern persists into the 18th century despite the substantial increase in the number of projects available after 1690. After 1760, however, the pattern changes. From that point until 1830, roughly 35% of all major projects were overseen by a chief engineer who had not already overseen a major project. The second series in Figure 10 (filled circles) shows the

number of first time projects by individuals who had not previously trained under a more experienced engineer.⁷⁰ After 1760, we can see that very few projects were overseen by engineers who did not either have prior experience or training under a more experienced engineer. Thus, the engineers chosen to oversee major projects were becoming a more experienced group.

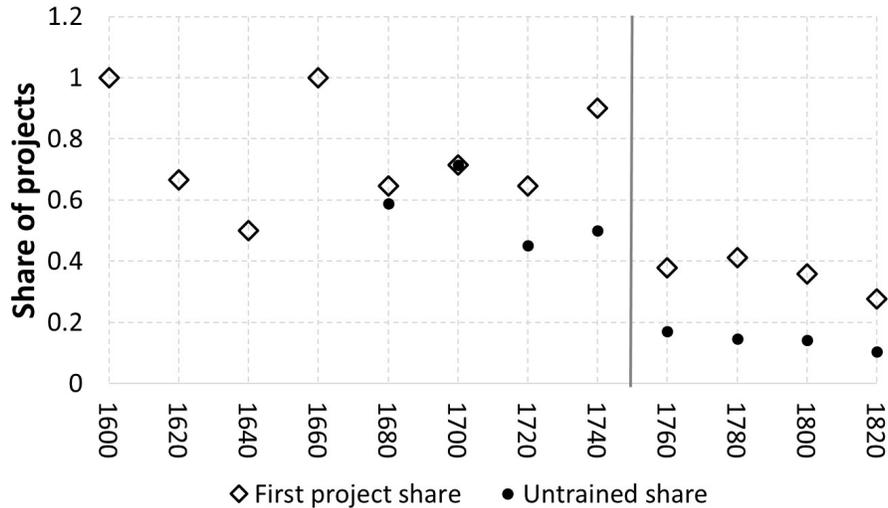


Figure 10: Changes in the structure of the civil engineering profession

Source: Author’s calculations using data from Skempton *et al.* (2002) Appendix II. Engineers are identified as having trained under a more experienced engineer if they had either worked for an engineer who had previously overseen one of the major projects on Skempton’s list or were partnered with such an engineer on their first major project.

Table 50 lists the top three individuals in each period and the number of projects they oversaw for each half-century from 1500. Below the top three, I also provide the mean number of major projects across all individuals in each period as well as the ratio of the number of projects done by the top individual and the top three individuals to the mean. These statistics provide a sense of the extent to which the

⁷⁰This data set is generated through a laborious manual review of the biographies of every engineer that oversaw a major project in the data. I begin the graph in 1680 because before that point I am not confident that the available biographical information is detailed enough to identify the training for most engineers.

distribution of projects across individuals was becoming skewed.

1500-1549			1550-1599		
Top individuals:	John Thompson	1	Top individuals:	Jacopo Aconcio	1
	Richard Cavendish	1		John Trew	1
	Thomas Franche	1		Joas Johnson	1
Mean projects per individual (all)		1	Mean projects per individual (all)		1
Ratio of top/mean		1	Ratio of top/mean		1
Ratio of top three/mean		3	Ratio of top three/mean		3
1600-1649			1650-1699		
Top individuals:	Cornelius Vermuyden	3	Top individuals:	John Hadley	3
	John Liens	2		Thomas Fitch	2
	Hugh Myddleton	1		Edmund Dummer	2
Mean projects per individual (all)		1.33	Mean projects per individual (all)		1.26
Ratio of top/mean		2.25	Ratio of top/mean		2.38
Ratio of top three/mean		4.50	Ratio of top three/mean		5.55
1700-1749			1750-1799		
Top individuals:	John Reynolds	4	Top individuals:	John Smeaton	18
	Thomas Steers	4		William Jessop	15
	Humphrey Smith	3		John Rennie	9
Mean projects per individual (all)		1.45	Mean projects per individual (all)		2.20
Ratio of top/mean		2.76	Ratio of top/mean		8.19
Ratio of top three/mean		7.60	Ratio of top three/mean		19.11
1800-1830					
Top individuals:	Thomas Telford	26			
	John Rennie	17			
	John Rennie Jr.	9			
Mean projects per individual (all)		2.62			
Ratio of top/mean		9.94			
Ratio of top three/mean		19.88			

Table 50: Leading civil engineers by period and their share of projects

Source: Author's calculations using data from Skempton *et al.* (2002) Appendix II.

K Government and the engineering profession

The government never played the central role in the British engineering profession that it did in other countries, most notably France. There, (military) engineers were deeply embedded in the state, which also oversaw the leading engineering schools, and as a result the engineers that they produced directed their attention first and foremost at solving the problems of importance to the military or the state.⁷¹

Addis (2007) contrasts the role of government in France and Britain in the development of civil and building engineering (p. 237):

The civil engineering profession in Britain developed very differently from its counterpart in France. In Britain, there were formal systems for educating and training military engineers, but the state played no part in establishing similar systems for civil engineers until the late nineteenth century. There was also very little state patronage of civil engineering works...By contrast, the scope of the civil engineer's role in France was defined largely by the king and his government's plans for establishing the French nation.

The main way that government influenced the development of the engineering profession was as a source of demand for engineering services. Here the Royal Navy was particularly important. The most famous example is the Portsmouth Dockyard, where Henry Maudslay gained experience building machinery designed by Mark Isambard Brunel under the direction of Samuel Bentham.⁷² Even this influence, however, was relatively modest compared to the enormous demand coming from private works, ranging from canal and railway companies to coal mines and textile factories.

⁷¹See Lundgreen (1990) and Alder (1997), particularly p. 9-11.

⁷²While both Maudslay and Brunel appear in the patent record as engineers, Samuel Bentham, brother of the more famous Jeremy, appears as an esquire in the majority of his seven patents.